The Impact of Risk and Farm Program Design on Cash Rents

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The incidence of agricultural subsidies determines the ultimate beneficiaries of farm programs and hence has important implications for farm policy. If the mix and relative weights of various US programs for commodity support – e.g., Title I payments, Federal crop insurance support, disaster assistance – were to change over time, there is the possibility that subsidy incidence may be affected even if total support levels are unchanged.[1] That is, the portion of agricultural subsidies that are capitalized into farmland values and rents may go up or down. Although several studies have considered the impact of farm programs on farmland values and rents, very few studies have considered the impact of price and yield risk.

In this study we estimate the joint impact of price and yield risk and farm program design for major agricultural commodities on cash rents for cropland. We hypothesize that farm programs increase rents through both income and risk reduction effects, and estimate the magnitude of each effect. In general our findings are in line with our hypothesis.

Background

A variety of Federal policies may lead to higher mean income for eligible farmers. Some of these policies are provided under Title I of the 2008 Farm Act (e.g., direct, countercyclical, loan deficiency, and Average Crop Revenue Election's [ACRE] revenue payments) or through disaster assistance (*ad hoc* or through the now expired Supplemental Revenue [SURE] program). Federally subsidized crop insurance can be actuarially super-fair for many farmers so that insurance, too, can increase mean income for eligible farmers. Current Title I polices in the 2008

[1] We do not directly consider legislation that supports biofuel production, but only direct supports. The benefits to farmers of biofuel legislation are felt in our model via its impact on prices.

Farm Act expire at the end of the 2012 crop year, and the future Title I policies are uncertain as of this writing, as are other Farm Act Titles that may interact with Federal crop insurance and/or with Title I policies.

There is long standing evidence that some portion of the benefits of government payments are capitalized into farmland rents (Floyd, 1965). Yet, the actual level of incidence depends on a number of factors, including the supply of land, input elasticities, prevailing expectations of future government payment levels, and the nature of the tenant-landlord relationship. Chambers (1995) cautions that even under the limited assumptions of a static general equilibrium model, the incidence of agricultural policies can be difficult to predict.

Most current commodity support programs may lead the recipient to not only have higher farm income but also reduced income variability, where "variability" is loosely defined here to include second and higher moments of income. A number of previous studies suggest that government payments contribute to farmland values and rents, yet the empirical methods employed presume risk neutrality (Kirwan, 2009; Goodwin *et al.*, 2011). Economic principles suggest that if producers are not risk neutral, income variability will be reflected in rental rates. Hence, farm support payments might increase cash rents not only by increasing income, but also by decreasing variability of income. Empirical studies in the agricultural economics literature often reject risk neutrality (Moschini and Hennessy, 2001; Serra *et al.*, 2006), suggesting that models not taking into account risk preferences will likely be misspecified.

A number of studies explicitly address the role of risk reduction in estimating the relationship between government programs and rental rates, yet these studies do not rely on microeconomic data. Krause and Brorsen (1995) use a state level repeated cross-section timeseries analysis and find that risk has a significant impact on cash rents but a small elasticity. Chavas and Thomas (1999) used national data to show that farmland prices do not reflect risk neutrality, which suggests that rents would also reflect risk. Katchova *et al.* (2002) use county level data from Illinois to determine the impact of risk on farmland values and returns and find that riskier counties have lower land values and returns.

Model

We use a standard farm decision model within an expected utility framework (e.g., Just 1974, Chavas and Holt 1990, Coyle 1992) accounting for both yield and price variability, as the theoretical basis for our analysis, but also relax its assumptions. Prices and yields are treated as stochastic in our model, and if producers are not risk neutral, the distributions of yield and price will impact rental rates. Yields of feasible crops are denoted by Y_i and output prices by p_i. Costs are denoted by c_i. Farmers select a vector of crops to plant and inputs to use, $\mathrm{x_i}$. We consider the economic rent (profits), π, that is derived from farmland to be the result of producers (tenant farmers) maximizing a concave von Neumann Morgenstern utility function over wealth. Using the Chavas and Holt (1990) EU framework, a representative tenant farmer at the county level faces the following objective function:

$$\max_{X_i} \pi = EU\left(\frac{I}{q} + p_i y_i(x_i) - c_i(x_i) + \varepsilon_i\right),$$

where *I* is exogenous wealth and *q* is a price index for household goods. The farmer solves the optimal x_i^*, which is a function of c_i , $E(R_i)$, and σ_{R_i}, where R_i is revenue, or, $y_i \cdot p_i$, and σ_{R_i} represents the covariance matrix of crop revenues. Without data to estimate wealth at the county level, we proxy for wealth via USDA crop reporting district (CRD) fixed effects dummies, where *CRD*s represent aggregations of several adjacent counties. Our model keeps costs c_i and expected revenue R_i separate in the estimation given that there is a potential for significant noise and/or bias in county level cost per acre estimates due to the greater regional aggregation of available cost data. In addition, for the crops that we consider, most costs are known at planting time. Hence, we assume that costs are nonstochastic, as in Just (1974).

The rent charged by landowners is a function of the *economic rent,* which is the random variable π^*, and if we assume that producers focus only the first two moments of revenue, rent $r = f\left(\pi_i^*\left(c_i, E(R_i, G_i), \sigma_{R,G_i}\right)\right)$, where G_i is government support in various forms. We assume that f is increasing in π and is a function of the decisions made by producers to maximize their expected utility, which are a function of our revenue and cost parameters. Hence we can estimate a reduced form model where $r = f\left(c_i, E(R_i, G_i), \sigma_{R,G_i}, CRD, Z_i\right)$, where Z_i represents factors not captured in our estimates of $E(\cdot)$ and σ .

We use a general empirical specification where we make no assumptions on the risk aversion of the landowner or whether or not the landowner captures the full economic rent. Our reduced form parametric empirical model that is nested in our more general specification is as follows: $r_t = \alpha_i + \Sigma_j \beta_{ij} R_{jt} + \Sigma_i \delta_{ij} C_{jt} + \Sigma_{k \geq j} \Sigma_j \gamma_{ijk} \sigma_{jt} + \Sigma_t \eta_t Gov_{it} + \theta_i t + \tau_i A_{it-1} + \Sigma_m \lambda_m CRD_m + \varepsilon_t$, where R_{jt} is expected revenue per acre, C_{jt} is cost per acre, σ_{ikt} are covariances of revenue, and Gov_{lt} is government support, including expected insurance indemnities, countercyclical payments and direct payments not included in R_{jt} (i.e., R_{jt} and σ_{ikt} already account for the commodity loan rate). In principle, R_{jt} could contain the net expected Federal crop insurance indemnity, but the wide variety of available Federal crop insurance instruments and coverage levels suggest that is it better for practical purposes to keep separate from revenue in estimation. Other variables include lagged acreage (A_{it-1}), the time trend, and regional dummies (*CRD)*. We do not include σ_{ij}, $i \neq j$ in our empirical estimation because markets most likely do not appreciate the covariance of revenue of different crops. Lagged acreage shares, (A_{it-1}), are included to account for the importance of individual commodities in determining rental rates.

We regress farm level cropland rents from 1999 to 2010 on county level measures of the first and second moments of total revenue (gross revenue plus net farm support payments) for all counties in the U.S. that produce corn and soybeans only (out of the choice set of primary crops comprised of corn, soybeans, spring and winter wheat, and upland cotton) and in a separate regression for all counties in the U.S. that produce corn, soybeans, and winter wheat only (out of the same choice set of primary crops). To reduce the prospects for misspecification bias, our general model is estimated using semi-nonparametric (SNP) regression techniques.

Our regression model nests a standard parametric expected utility model under risk aversion but allows additional flexibility through the additional SNP transformations of the mean and standard deviation of revenue variables. Derivatives and elasticities of the estimated regression model with respect to these two variables help to identify the impacts of mean versus revenue variability on cash rents. Statistical analysis of the estimated elasticities using the paired bootstrap approach addresses the significance of the mean and variance of revenue, and hence risk preferences, on cash rents. Our bootstrap method allows for flexible right-hand-side regression modeling and for modeling interactions between variables. In particular, we use a paired bootstrap approach in a resampling methodology that involves drawing *i.i.d.* observations with replacement from the original data set (Efron 1979; Yatchew 1998), maintaining the pair-wise relationship in each observation between the variables, e.g., variable values y_i and x_i are always kept together as a row. The bootstrap data-generating mechanism is to treat the existing data set of size T as a population from which G samples of size T are drawn. The regression equation is re-estimated for each of these bootstrapped data sets. Variation in estimates results from the fact that upon selection, each data point is replaced within the population. With use of the bootstrap approach, we do not have to depend on the estimated covariance for measuring statistical fit of a function that can have relatively high collinearity between the explanatory variables due to the inclusion of economic variables that tend to be correlated, and due to the addition of transformation variables from the SNP specification. Instead, we draw our measures of fit for the coefficient estimates, which are consistent even under collinearity.

The Fourier functional form we used for the SNP is the only functional form known to have Sobolev flexibility, so the difference between the model $A^{SNP}(x,\theta)$ and the true function $f(x)$ can be made arbitrarily small for any value of x as the sample size increases (Gallant, 1987; Fenton and Gallant, 1996). The Fourier flexible functional form, which attaches linear and quadratic terms to the Fourier terms to decrease the terms needed to model nonperiodic functions, is specified as

$$r_t^{SNP}(x,\theta_k) = U_0 + \boldsymbol{b}'\boldsymbol{x} + 0.5\boldsymbol{x}'\boldsymbol{D}\boldsymbol{x} + 2\sum_{\alpha=1}^{A}\left\{\sum_{j=1}^{J}\left(v_{j\alpha}\, cos[j\boldsymbol{k}'_{\alpha}\boldsymbol{s}(\boldsymbol{x})] - w_{j\alpha}\, sin[j\boldsymbol{k}'_{\alpha}\boldsymbol{s}(\boldsymbol{x})]\right)\right\}$$

where (k-A-J) x 1 vectors b and x are the set of coefficients and variables, respectively, in equation 2, $U_0 = u_0 + \sum_{\alpha=1}^{A}\{u_{0\alpha}\}$, and $D = \sum_{\alpha=1}^{A} u_{0\alpha} k_{\alpha}' k_{\alpha}$, k is the dimension of θ, A (the length) and J (the order) are positive integers, and k_α are vectors of positive and negative integers that form indices in the conditioning variables, after shifting and scaling of x by $s(x)$. The function $s(x)$ prevents periodicity in the model.

Data

We construct distributions for county level expected farm revenue as a function of both crop revenue and farm support, including crop insurance premium subsidies, indemnities and Title I support. County level data for corn, soybeans, winter wheat, and hay from 1989-2010 were used. Yield distributions are estimated non-parametrically using USDA-NASS county level data (Cooper and Arnade, 2011). Price distributions are derived non-parametrically from futures market data (*ibid*.). Price and yield densities were converted into within-season deviates (Cooper, 2010), and the price deviate was derived from (harvest price-planting price)/planting price. The yield deviate was derived from (actual yield-expected yield)/expected yield.

The estimated price and yield distributions, with historic correlations imposed between them, are used to construct the first and second moments of revenue for each farmer. Government support in the form of marketing loan benefits (e.g., loan deficiency payments) are included in the revenue measures while expected net insurance indemnity payments, Direct Payments (DPs), and expected Counter-Cyclical Payments (CCPs) are included as separate regressors. DPs and CCPs are included as separate variables from revenue as they are product nonspecific support that cannot reasonably be attributed to current revenue of any particular crop (in addition to not being tied to current production). The expected net insurance indemnity payments – which are positive given the premium subsidies – are treated as separate variables given that many assumptions are needed to generate their expected value (the coverage rate is one example). The previous ten years of data were used to generate the means and variances of revenue for each year, with the econometric analysis covering 1999-2010. Our two econometric specifications are conditional on counties having growing histories for our specific crops.

Rental data is from the National Agricultural Statistics Service's (NASS) June Area survey, which is the USDA's primary source of information on farmland rents throughout the United States. The survey is designed to be representative at the state and national level. About 11,000 segments (approximately 1 square mile) are selected using spatial sampling methods and an area frame that stratifies all agricultural lands by land use type. Segments remain in the sample for five years, such that each year one-fifth of the segments rotate out of the sample. Operators of all tracts (or fields) in each segment are interviewed during the first two weeks of June, yielding approximately 35,000 tract-level observations annually.

Cropland rents reported by tract operators are averaged at the county level for our analysis. For some states where irrigation is uncommon, per acre rents are collected for all cropland. In other cases, rent is collected for both irrigated and non-irrigated cropland. Because there is no way to weight rental rates, a simple average of both irrigated and non-irrigated cropland rent is used when both are reported. We require at least three rental rate observations per year per county to aggregate rents to the county level. Survey weights are not used because they are not designed for aggregation at the county level.

Results

We first consider all counties with a history of corn and soybean production. Results from parametric and semi-nonparametric estimation are reported in Table 1. For the sake of clarity, the tables show only the regression results for coefficients that are likely to be of policy interest; e.g., regression results for fixed effects and lagged acreage shares are not shown. Also, to reduce the burden of displaying the large number of SNP coefficients, which do not individually have economic interpretations, the coefficient results are expressed as Dy/Dx (which of course are the same as the coefficients in the linear parametric model). Both models have strong explanatory power, with R^2 of 0.80 and 0.83, respectively. Rent appears to be inelastic to almost all of our explanatory variables. This is not surprising, as although rent can be renegotiated annually, most rental arrangements are multi-year.

Expected revenues for both corn and soybeans have statistically significant and large impact on rental rates. For both models, corn revenue has a larger impact on rent than soybean revenue. The standard deviation (variability) of corn and soybean revenue has a smaller elasticity than revenue. We expect standard deviation to have a negative sign, and this holds for the semi-nonparametric model only. Overall the relationship between rents and expected revenue is much more robust than the relationship between rents and revenue variability. Inputs costs for corn have the expected sign, but are statistically significant only in the parametric model. Soybean costs are excluded from our model because they are highly collinear with corn costs. Higher countercyclical payments are usually associated with higher rents, but results are not always statistically significant across the different models.

A priori, it is somewhat difficult to say what would be the impact of the expected net insurance indemnities on rent. On the one hand, higher expected revenues mean higher insurance premiums – and the total dollar value of insurance premium and A&0 (administrative and operating) subsidies – but so does higher revenue variability, though in general, the latter's impact on premiums is higher than the former's. Hence, higher net indemnities might be indicative of regions with lower rental values. Our regression results for this variable suggest little (identifiable) impact of this variable on rent. Further, the direction and magnitude of the impact of insurance indemnities is highly sensitive to functional form.

In contrast, the linkages between Direct Payments and rents should be more transparent. In fact, the coefficients on this variable are positive and significant at the 1 percent level in each case, suggesting that pass-through of these payments to rent is occurring. In one case, the coefficient is greater than 1, but this could be reflective of the importance of direct payments to farmers securing loans at favorable rates.[2] We would also expect this statistically significant relationship because direct payments are known in advance.

We also consider counties that have corn, soy and winter wheat production. Because wheat is generally grown in areas with more diverse climatic conditions, we expect results to be different than those of counties with a history of corn and soy production. Results from parametric and semi-nonparametric estimation are reported in Table 2. Both models have strong explanatory power, with R^2 of 0.70 and 0.73, respectively. Rent is inelastic to almost all of our explanatory variables, and overall the results are not a major departure from our estimation with corn and soy counties.

Expected revenues for all crops are strongly statistically significant, although corn revenues have a much larger elasticity than soy and wheat. The impact of the standard deviation (variability) of revenue on rent is highly sensitive to the functional form, and the variability of corn even has a sign change across models. The variability of soybean revenue is statistically significant for at least the 10% level for both specifications, and, as would be expected, has a negative sign across both models. The results for variability of revenue for the semi-nonparametric model appear to be closer to what would be expected, but for both

[2] Also, Direct Payments are increasing in the historical productivity of the land via “base” yields, and current productivity is likely to be correlated with historic productivity. Future analysis could seek to provide instruments to account for this effect.

models variability of revenue appears to have a much smaller and less robust of an impact on rents than expected revenue.

Similar to standard deviation of revenue, costs for corn and wheat do not have the expected sign and vary significantly across both models. For the semi-nonparametric model, rent appears to be highly elastic in response to corn and wheat costs. This could be due to higher costs capturing increased input use on higher quality land, and in future research we will explore potential causes of this result. Costs per acre also had inconclusive impacts in our specification with corn and soy counties. Depending on the crop scenario and empirical model, the coefficients are positive or negative and significant, or insignificant. One limitation of cost variables in this application is that costs per acre at the county level are not available, and we must depend on fixed effects to provide the county specific effects. Secondly, practical limitations in collecting cost per acre data may mean that available cost per acre data per crop is not fully crop specific. In sum, costs per acre are a variable for which we expect weak econometric results.

Corn and soy countercyclical payments have a small and statistically insignificant effect on rents, but wheat countercyclical payments have a larger and statistically significant effect at the 1 percent level. This may be due to countercyclical payments being more important for wheat production. As with our estimation for corn and soy counties, expected indemnities in most cases do not have a large or statistically significant impact on rents. Likewise, direct payments have a highly statistically significant impact on rents that has a similar elasticity to that of expected revenues.

Conclusion

Our paper advances the literature through consideration of the impact of risk on cash rents using microdata, as well as analysis of how farm programs influence rents through both their income increasing and risk reducing effects. We find that expected revenues have a significant impact on rents, but are inelastic, as are most of our explanatory variables. The variability of revenues also impact rental rates, but the impact is smaller than that of expected revenue and the direction and robustness of this effect vary across different models. Direct payments have a large impact on rents, as do countercyclical payments for wheat. To some extent, the relatively low impact of revenue variability could be due to the presence of federal commodity support. The potential income-augmenting and risk reducing effects of marketing loan benefits are directly included in our estimates of the mean and variability of revenue, and the coefficients estimates on these variables should be reflective of the impacts of this support on rents. The other support programs are treated as variables separate from rent for the reasons that we discuss in the main text.

Future work on this study will involve simulating the impact of changes to farm programs and using field level rental data instead of county-level aggregated data. Assumptions regarding our functional form can also be tested, as could different representations of revenues, government payments and costs.

References

Chambers, R.G., 1995. The incidence of agricultural policies. Journal of Public Economics 57, 317-335.
Chavas, J.P., Holt, M.T., 1990. Acreage decisions under risk: the case of corn and soybeans. American Journal of Agricultural Economics 72, 529-538.

Chavas, J.P., Thomas, A., 1999. A dynamic analysis of land prices. American Journal of Agricultural Economics 81, 772-784.
Cooper, J., Arnade, C., 2011. Globally Flexible Modeling of County-Level Acreage Response for Primary US Field Crops. Agricultural and Applied Economics Association Annual Meeting, Pittsburgh.
Cooper, J.C., 2010. Average Crop Revenue Election: A Revenue-Based Alternative to Price-Based Commodity Payment Programs. American Journal of Agricultural Economics 92, 1214-1228.
Coyle, B.T., 1992. Risk aversion and price risk in duality models of production: a linear mean-variance approach. American Journal of Agricultural Economics 74, 849-859.
Efron, B., 1987. Better bootstrap confidence intervals. Journal of the American Statistical Association, 171-185.
Fenton, V.M., Gallant, A.R., 1996. Qualitative and asymptotic performance of SNP density estimators. Journal of Econometrics 74, 77-118.
Floyd, J.E., 1965. The effects of farm price supports on the returns to land and labor in agriculture. The Journal of Political Economy 73, 148-158.
Gallant, A.R., 1987. Identification and consistency in semi-nonparametric regression. In: Bewley, T.F. (Ed.), Advances in Econometrics: Fifth World Congress. Cambridge University Press, pp. 145-170.
Goodwin, B.K., Mishra, A.K., Ortalo-Magné, F., 2011. The Buck Stops Where? The Distribution of Agricultural Subsidies. National Bureau of Economic Research.
Just, R.E., 1974. An investigation of the importance of risk in farmers' decisions. American Journal of Agricultural Economics 56, 14-25.
Katchova, A.L., Sherrick, B.J., Barry, P.J., 2002. The Effects of Risk on Farmland Values and Returns. American Agricultural Economics Association Annual Meeting, Long Beach.
Krause, J.H., Brorsen, B.W., 1995. The effect of risk on the rental value of agricultural land. Review of agricultural economics, 71-76.
Moschini, G., Hennessy, D.A., 2001. Uncertainty, risk aversion, and risk management for agricultural producers. Handbook of Agricultural Economics 1, 88-153.
Serra, T., Zilberman, D., Goodwin, B.K., Featherstone, A., 2006. Effects of decoupling on the mean and variability of output. European Review of Agricultural Economics 33, 269-288.
Yatchew, A., 1998. Nonparametric regression techniques in economics. Journal of Economic Literature 36, 669-721.

Tables

Table 1. Counties with Corn and Soy Production

	Parametric (OLS)		Semi-Nonparametric (Fourier)	
	Rent(dY/dx)	**Elasticity**	**Rent (dY/dx)**	**Elasticity**
Constant	11.44	-	77.78	-
	(6.58)		(53.49)	
Corn Revenue	0.19	0.79	0.15	0.61
	(0.01)***	(0.05)***	(0.02)***	(0.07)***
Soy Revenue	0.09	0.28	0.15	0.49
	(0.02)***	(0.06)***	(0.02)***	(0.07)***
SD Corn Rev	0.06	0.05	-0.09	-0.08
	(0.04)	(0.03)	(0.05)**	(0.04)**
SD Soy Rev	-0.10	-0.06	-0.09	-0.05
	(0.06)*	(0.03)*	(0.06)	(0.04)
Cost Corn	-0.27	-1.03	-0.03	-0.11
	(0.02)***	(0.07)***	(0.06)	(0.24)
Corn CCP	0.14	0.01	1.70	0.17
	(0.15)	(0.2)	(0.60)***	(0.06)***
Soy CCP	0.98	0.23	-1.81	-0.04
	(0.39)**	(0.01)**	(1.51)	(0.04)
Corn E(Indemnity)	-0.61	-0.02	-0.41	-0.01
	(0.23)***	(0.01)***	(0.31)	(0.01)
Soy E(Indemnity)	1.14	0.01	-0.55	-0.01
	(0.38)***	(0.00)***	(0.69)	(0.01)
Direct Payments	0.98	0.27	1.23	0.33
	(0.09)***	(0.02)***	(0.15)***	(0.04)***
R^2	0.803		0.826	
Observations	3489		3489	

*,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2. Counties with Corn Soy, and Winter Wheat Production

	Parametric (OLS)		Semi-Nonparametric (Fourier)	
	Rent (dY/dx)	**Elasticity**	**Rent (dY/dx)**	**Elasticity**
Constant	4.24	-	1123.09	-
	(8.36)		(1119.89)	
Corn Revenue	0.04	0.45	0.09	0.44
	(0.01)***	(0.04)***	(0.01)***	(0.05)***
Soy Revenue	0.06	0.23	0.05	0.17
	(0.01)***	(0.05)***	(0.01)***	(0.05)***
WW Revenue	0.03	0.10	0.07	0.22
	(0.01)***	(0.02)***	(0.01)***	(0.04)***
SD Corn Rev	0.05	0.06	-0.04	-0.04
	(0.02)***	(0.02)***	(0.03)	(0.03)
SD Soy Rev	-0.06	-0.05	-0.13	-0.10
	(0.03)*	(0.03)*	(0.04)***	(0.03)***
SD WW Rev	0.14	0.09	0.07	0.05
	(0.03)***	(0.02)***	(0.04)	(0.03)
Cost Corn	0.05	0.24	0.85	4.01
	(0.03)*	(0.13)*	(0.34)**	(1.59)**
Cost WW	-0.16	-0.62	0.54	2.06
	(0.03)***	(0.10)***	(1.60)	(6.07)
Corn CCP	0.12	0.01	0.40	0.05
	(0.10)	(0.01)	(0.50)	(0.06)
Soy CCP	0.32	0.01	-0.43	-0.01
	(0.25)	(0.01)	(1.77)	(0.05)
WW CCP	1.48	0.12	6.04	0.49
	(0.16)***	(0.01)***	(1.64)***	(0.13)***
Corn E(Indemnity)	-0.22	-0.01	0.10	0.005
	(0.11)**	(0.01)**	(0.18)	(0.01)
Soy E(Indemnity)	-0.03	-0.001	0.10	0.002
	(0.19)	(0.004)	(0.35)	(0.01)
WW E(Indemnity)	-0.14	-0.005	0.38	0.01
	(0.11)	(0.004)	(0.25)	(0.01)
Direct Payments	0.71	0.23	1.15	0.37
	(0.09)***	(0.03)***	(0.11)***	(0.04)***
R^2	0.702		0.730	
Observations	5442		5442	

*,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.