The Feasibility of Area-wide Pest Management under Heterogeneity and Uncertainty: The Case of Citrus Health Management Areas

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Introduction

Huanglongbing (HLB) or citrus greening disease is a major bacterial disease that affects citrus trees in Florida and throughout citrus producing regions worldwide. In Florida and elsewhere, the disease is a major source of revenue loss for citrus growers. The Asian citrus psyllid, a sap-sucking insect, spreads the disease by feeding on infected trees and then transmits the disease to healthy trees. Symptoms of the disease begin benignly with yellow leaves but progress over time and include bitter, economically useless fruit (Brlansky et al. 2011).

There is currently no effective treatment for the disease, although a wide variety of treatments are being tested. Primary control measures include applying insecticides to control the insect vector, applying nutrients through foliar applications to mitigate the nutrient deficiencies caused by the disease, and more recently, the use of antibiotics and antimicrobials have been used through a temporary allowance by the Environmental Protection Agency (Gottwald et al. 2012, Putnam 2016).

The movement of psyllids spreads the disease both within and between blocks of citrus trees. Due to movement beyond the range of a single grower's fields, Citrus Health Management Areas or CHMAs have been created in Florida. Insecticide applications within the CHMA are coordinated by a grower coordinator in conjunction with a University of Florida extension agent. The plans usually include four to nine insecticide applications applied throughout the year, and list the active ingredient to be applied and the time range for each application.

Coordinated applications should be more effective at reducing pysllid counts than asynchronous applications, and the plans are designed to minimize insecticide resistance. Despite these features, CHMA participation rates and coordination efforts vary tremendously across

Florida. This paper seeks to determine the effects of varying participation and control effort on psyllid populations and to determine if broader geographical coordination is necessary.

Previous Work

Previous work in this area falls into three main categories: optimal pest control in general, spatial-dynamic models of invasive species management, and dynamic models of pest and disease control in perennial systems. A large body of literature analyzes optimal pest control decisions considering risk, pesticide externalities, pesticide resistance, and intra- and inter-seasonal insect dynamics (Feder 1979; Feder and Regev 1975; Plant, Mangel, and Flynn 1985; Regev, Shalit, and Gutierrez 1983, Lichtenberg and Zilberman 1986; Saha, Shumway, and Havenner 1997; Regev, Gutierrez, and Feder 1976). However, much of this work considers annual crops, which are removed at the end of each growing season. Perennial crops remain in the ground for many years, creating a stock of diseased trees that carries over across growing seasons. Additionally, perennial crops usually entail a larger initial investment with the expectation that the investment will produce yields for many years. The threat of disease is then potentially more severe.

Models of invasive species management generally model the spread of the species across a landscape and assume that management options include containment and/or eradication (Epanchin-Niell and Wilen 2012; Epanchin-Niell and Wilen 2014; Liu and Sims 2016; Marten and Moore 2011; Olson and Roy 2002; Saphores and Shogren 2005; Sharov and Leibhold 1998) For the case of HLB in Florida, containment and eradication are no longer feasible options, and the disease is considered established throughout the state. Management of established vector populations within groves and between groves is a more relevant issue for HLB than prevention of invasion of new groves.

Dynamic models of pest and disease in perennial systems include dynamic models of disease control in an individual field (Grogan and Mosquera 2015) and optimal rotation length or harvest volumes in the presence of disease (Aadland et al. 2015; Roosen and Hennessy 2010). Some work has spatial features of pest management, including Atallah et al. (2015), which considers a spatially optimal pattern of control of grapevine leafroll disease within a given field, and Brown et al. (2002), which considers management of Pierce's Disease as a function of distance from riparian vegetation that serves as a source of the disease's insect vector. Among these models, only Brown et al. (2002) consider an insect-vectored disease, but for the case of Pierce's Disease, insecticide control is not an option; management of riparian habitat and construction of barrier habitat are the primary control options. This lessens the ability of growers to coordinate and instead requires coordination between managers of riparian habitat and growers. While most work in this area has utilized theoretical models, Grogan and Goodhue (2012) empirically indentify the presence of spatial externalities in the California citrus industry. Applications of certain insecticides reduced populations of an economically important parasitic wasp, lowering growers' ability to use the wasp for pest control.

To the best of our knowledge, no work has yet considered the efficacy of coordinated control of an insect-vectored disease of a perennial crop.

Data

For this study, we surveyed CHMA grower coordinators to pair with existing psyllid count data and information from CHMA websites. We collected information regarding when the CHMA was formed; if the CHMA is still coordinating insecticide applications, and if not, when coordination stopped; grower participation rates over time; and the effectiveness of CHMA coordination in terms of reduced disease spread, reduced disease severity, and reduced pysllid counts. We also asked coordinators what kinds of information or tools they needed to improve participation and efficacy. Out of the 55 CHMAs that have ever existed, 54 have persisted through our sample period. Of those 54, 41 had viable grower coordinator contact information available and 16 responded with usable responses, yielding a 39% response rate. Psyllid count data and parcel sizes for individual fields were obtained from the CHMA IFAS website for citrus growers, and CHMA land area and border length was calculated using data from the Florida Department of Agricultural and Consumer Services Ag-Apiary Mapping Program.

Table 1 reports plot-level summary statistics for data obtained for all CHMAs, and also separately reports the statistics for plots in CHMAs included among survey respondents. Table 2 reports CHMA-level summary statistics for pertinent variables obtained through the grower coordinator survey. Figure 1 plots the number of psyllid counts averaged over all plots with a count during that cycle. The graph demonstrates that there is a cyclical nature to the psyllid population, and beginning in 2014, the peak of the cycle has been increasing.

Methods

The analysis would ideally use two layers of spatial analysis. The first would consider CHMA-level impacts on psyllid populations as a function of CHMA characteristics. The second would aggregate plot-level data up to the Public Land Surveying System's section unit (1 square mile) because that is the finest scale on which spatial referencing is available. Unfortunately, the spatial model for the latter level of analysis is still in progress. With the large number of observations, spatial model convergence has been problematic. The analysis that follows utilizes CHMA-level measures of psyllid counts only.

For all analyses, the raw psyllid count data represent censored data. Scouts tap randomly selected branches and count the number of psyllids that fall from the tree onto a white platform held under the branch. The count data will be positively correlated with psyllid populations, but for some low population level, the probability of detecting psyllids in any given tap becomes small. Consequently, a count of zero represents a range of low psyllid populations, and the analysis makes use of tobit models to account for this censoring.

In addition to censoring, there is reason to believe that observations are spatially correlated. The psyllid population itself is likely correlated across space; psyllids on one field may contribute to reproduction and psyllid populations on neighboring fields. Additionally, the error terms in the model may be spatially correlated if unobserved factors like climate, weather, or surrounding habitat via backyard citrus or abandoned groves influence psyllid populations. To account for spatial externalities, we construct a matrix based on adjacent CHMAs. The weighting assigned to each of CHMA i's directly adjacent neighbors is based on the percent of CHMA i's total shared border that is shared with each of its neighbors j such that:

$$w_{ij} = \frac{length_{ij}}{\sum_{k=1}^{K} length_{ik}} \tag{1}$$

Previous spatial analysis of disease incidence finds a median distance of 3.5 km so we do not expect spatial correlation beyond adjacent CHMAs (Gottwald 2010).

Due to the apparent changes in the psyllid population across the years in the sample, and anecdotal evidence about changing psyllid populations and changing efficacy of insecticide applications, the models are estimated for each year. For 2012 through 2016, the dataset represents a full year of data with seventeen to eighteen cycles of psyllid counts.

The base model is represented by:

$$y_{ict} = \rho W y_{ict} + X_{it}'\beta + \alpha_i + \gamma_c + v_{ict} \quad (2)$$

where y_{ict} is the statistic representing psyllid counts in CHMA i in cycle c in year t. W is a spatial weighting matrix with each weight as defined in equation (1), X_{it} is a vector of characteristics at the CHMA level, which can vary across years but are constant across cycles within a year. These characteristics will be discussed further below. For unobservable terms, we account for time-invariant unobservables at the CHMA level α_i, a spatially-invariant error term each count cycle γ_c, and a random error term in each CHMA, each cycle for year t, v_{it}.

We also allow for correlation in the error terms such that:

$$v_{ict} = \lambda W v_{ict} + u_{ict} \quad (3)$$

We hypothesize that ρ will be greater than zero, given potential positive effects of large psyllid populations on surrounding regions. We hypothesize that λ will also be positive due to the potential for spatially-correlated environmental attributes that might affect psyllid populations.

The explanatory variables considered in X_{it} include some variables specific to CHMAs whose grower coordinator responded to our survey and some applicable to all CHMAs. To control for possible bias in terms of overall psyllid populations, we include a dummy variable indicating if the CHMA's grower coordinator responded. We then interact that variable with four variables of interest: a dummy variable indicating whether or not the CHMA was coordinating applications in time *t*, a count variable indicating the number of years the CHMA had been coordinating up until year *t* with this variable equaling 0 if the CHMA was not coordinating in time *t*, a continuous variable representing the CHMA's grower participation rate in the previous year, and a count variable representing the number of coordinated insecticide applications planned by the CHMA in the previous season. The latter two variables are lagged to eliminate the possibility that psyllid counts in that year affect participation or number of applications. We do not include a lag of the coordination variable because plans to coordinate generally occurred well in advance in order to have time to plan applications with an extension agent and fellow growers. Variables obtained for all CHMAs include the total land area of the CHMA; larger CHMAs may be able to buffer themselves from neighboring CHMAs better. We also include the border to area ratio for each CHMA to control for the possibility that CHMA's with extensive borders could be more affected by their neighbors. Lastly, we include the average parcel size within the CHMA. Anecdotal evidence suggests that owners of larger citrus operations have more aggressively controlled psyllids.

Results

Three metrics were used to depict psyllid counts at the CHMA-level: median, mean, and 75th percentile of psyllid counts. The first model used the median psyllid count across all plots in each CHMA in each cycle. For the majority of CHMAs for years 2012 – 2015, the median value was actually 0. The percent of CHMA-cycle combinations with a value of zero remained similar for 2012 and 2013, and then steadily decreased through 2016, as overall psyllid counts increased throughout the state.

Table 3 reports the results of the median psyllid count spatial tobit models estimated by year. The first observation to note is that the responding CHMAs had higher median psyllid counts in all years but 2016. Coordinators with high psyllid populations may be more concerned about the success of their CHMA and may have been more inclined to respond. Among responding CHMAs, the number of years for which the CHMA has been actively coordinating insecticide applications is negatively correlated with psyllid counts for 2013, 2014, and 2015, suggesting that sustained efforts were effective in that time period. In 2012, there was too little variation in years of coordination, so this variable is not included, and the base *Currently Coordinating* variable is negatively associated with psyllid counts. Both of these trends suggest that CHMAs were effective.

In terms of the actions of the CHMAs, participation rates are negatively correlated with psyllid counts in 2012, which is as hypothesized, but positively correlated in 2014 and 2015. Similarly, the number of coordinated applications is positively correlated with psyllid counts in 2012, but negatively correlated in 2015. These results do not show strong support for CHMA efficacy varying based on participation rates or number of applications applied in terms of median psyllid counts.

However, a different picture emerges when considering the mean psyllid counts at the CHMA level in each cycle. This metric better accounts for CHMAs with some plots with large numbers of psyllids. As before, survey respondents have higher psyllid counts, and current coordination and longevity of coordination are negatively correlated with psyllid counts. Using mean counts, the number of coordinated applications is negatively correlated with psyllid counts for all years except for 2016, providing stronger support that the coordinated applications and their number were effective when considering plots with higher psyllid pressure. The insignificance of the variable in 2016 could be due to developing resistance among Florida psyllid populations. While median psyllid counts demonstrated little spatial correlation, the mean counts demonstrate strong spatial correlation both in terms of the psyllid counts themselves as well as the error term for 2014 and 2015. For 2013 and 2016, while the spatial coefficients are insignificant, the spatial autocorrelation model is still preferred to a non-spatial tobit.

Finally, the analysis considers the 75th percentile of psyllid counts to directly consider those plots that have higher than average psyllid counts. The results are similar to those found for mean psyllid counts with regards to number of coordinated insecticide applications. Applications are negatively correlated with psyllid counts for all years except for 2016. While *Currently Coordinating* and/or *Years of Coordination* were statistically significant for all years using mean counts, they are only significant for 2012, 2013 and 2014 when using the 75th percentile of counts. Base level coordination appears ineffective at managing higher psyllid populations in more recent years. In terms of spatial correlation, there is evidence of correlation using this metric for 2014 and 2016.

Conclusions

The results support the hypothesis that CHMAs effectively reduce psyllid populations. Base levels of coordination appear more effective for low to moderate psyllid pressure, while the number of applications applied appears relevant to determine efficacy for higher psyllid populations. Interestingly, by all metrics, CHMAs did not demonstrate much efficacy at reducing psyllid counts in 2016. This could be due to increasing resistance to the common insecticides developing among psyllid populations. This could also be due to a prevalence of abandoned groves serving as sources of psyllids, making insecticide applications less effective as psyllids from abandoned groves re-populate treated groves.

While we hypothesized that spatial correlation would be present across CHMAs, this correlation is not robust across years or psyllid count metrics. The current CHMAs appear to be encapsulating many of the spatial externalities that occur across fields within their boundaries.

Future work should consider data for 2017 when more rounds of count data are available to determine if the ineffectiveness of CHMAs found for 2016 persists into 2017. The analysis will also be expanded to section-level data to make use of the ample data provided by the CHMA program. This analysis will also consider regions of Florida to determine if spatial patterns vary across the state.

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Table 1. Summary Statistics of Data Obtained for All CHMAs

	Respondents				Whole Sample			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Plot-Level Statistics								
Psyllid Count	5.58	12.92	0.00	100.00	5.51	12.63	0.00	100.00
Any Directly Neighboring Plot	0.95	0.21	0.00	1.00	0.93	0.25	0.00	1.00
Parcel Size (Acres)	25.42	26.11	0.00	200.80	23.09	25.80	0.00	297.70
N	117,036				423,537			
CHMA-Level Statistics								
Total Land Area (1,000 Acres)	108.03	58.44	37.02	235.26	156.02	188.72	18.50	961.73
Border Length to Area Ratio	0.40	0.13	0.21	0.61	0.41	0.18	0.13	1.13
N	16				54			

Table 2. Summary Statistics of Survey Responses

Variable	Mean	Std. Dev.	Min	Max
Total Citrus Acres in CHMA	10625.00	8850.08	1000	30000
Participation Rate, if Active	60.98	27.79	1	100
Number of Coordinated Applications, if Active	3.85	2.21	1	8
Years of Coordination	4.94	1.61	2	7
Year Formed	2102	1.61	2010	2015

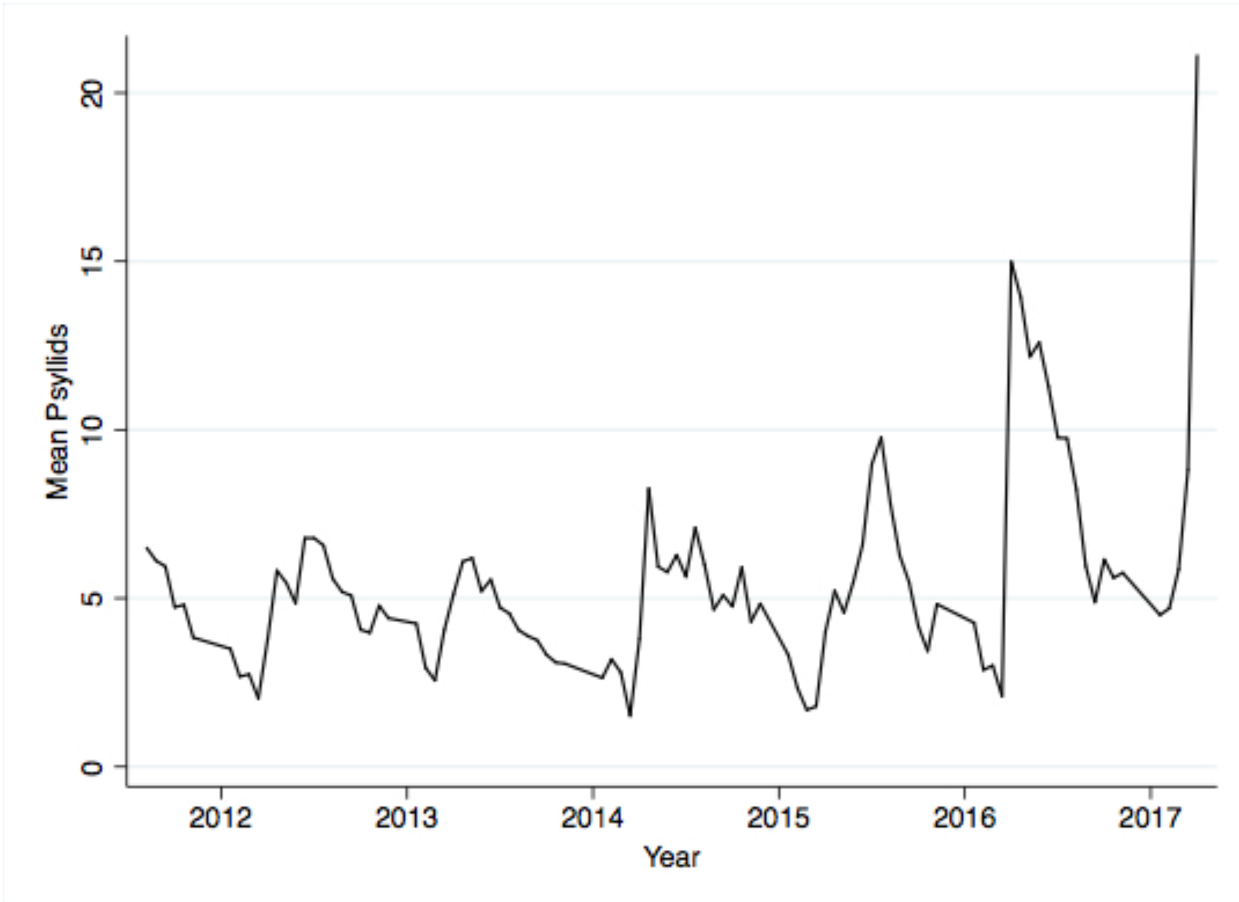

Figure 1. Average Number of Psyllids Trapped across All Plots in Florida over Time

Table 3. Spatial Tobit Model of Median Psyllid Counts at the CHMA-Level by Count Cycle

Median Psyllid Counts	2012	2013	2014	2015	2016
Survey Respondent (SR)	1.358***	2.468***	2.180***	2.072**	-0.431
	(0.448)	(0.580)	(0.755)	(0.855)	(1.320)
SR x Currently Coordinating	-1.472**	-0.733	-1.000	-0.834	1.654
	(0.574)	(0.728)	(0.631)	(0.743)	(1.563)
SR x Currently Coordinating x Years of Coordination		-1.559***	-0.837*	-1.017***	-0.043
		(0.457)	(0.461)	(0.362)	(0.298)
SR x Participation Rate, *t - 1*	-0.112**	0.042	0.047**	0.065***	-0.030
	(0.045)	(0.039)	(0.020)	(0.019)	(0.021)
SR x Number of Coordinated Applications, *t - 1*	2.018*	-1.404	-0.052	-0.223*	0.045
	(1.136)	(1.042)	(0.106)	(0.120)	(0.152)
Total CHMA Land Acres (1,000s)	-0.008***	-0.001	-0.002	0.002**	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CHMA Border to Area Ratio	-9.514***	-2.732*	2.758***	1.687	-2.247
	(2.057)	(1.464)	(1.049)	(1.402)	(2.246)
Average Parcel Acres	-0.053***	-0.077***	0.063***	-0.171***	0.046*
	(0.019)	(0.018)	(0.019)	(0.029)	(0.026)
Controls for Cycle	Yes	Yes	Yes	Yes	Yes
Constant	6.467***	3.584***	4.188	-4.978	11.030
	(1.584)	(1.245)	(1.101)	(1.360)	(2.044)
Rho	-0.032	0.077*	0.027	0.022	0.030
Lambda	0.057	-0.043	-0.009	-0.016	-0.050
Sigma	-3.840***	-3.591***	2.681***	-4.414***	6.456***
N	846	799	846	799	799
LR Test (Rho = 0)	0.459	2.867*	0.561	0.412	0.771
LR Test (Lambda = 0)	1.554	0.128	0.046	0.165	1.655
LR Test SAC vs. OLS (Rho + Lambda = 0)	4.716*	2.967	0.741	0.619	1.926
Wald Test	92.575***	65.248***	549.711***	6.295	434.670***
Number Censored	594	578	516	442	316

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Robust standard errors in parentheses

Table 4. Spatial Tobit Model of Mean Psyllid Counts at the CHMA-Level by Count Cycle

Mean Psyllid Count	2012	2013	2014	2015	2016
Survey Respondent (SR)	1.687***	2.173***	4.958***	2.311***	2.161**
	(0.388)	(0.448)	(0.590)	(0.629)	(1.017)
SR x Currently Coordinating	-2.163***	0.840	-1.435*	-1.142**	0.128
	(0.412)	(0.636)	(0.758)	(0.496)	(1.026)
SR x Currently Coordinating x Years of Coordination	0.918	-0.693***	-0.328	-0.809***	-0.487**
	(0.744)	(0.188)	(0.263)	(0.214)	(0.230)
SR x Participation Rate, *t - 1*	-0.003	-0.006	0.007	0.055***	0.001
	(0.011)	(0.009)	(0.014)	(0.012)	(0.013)
SR x Number of Coordinated Applications, *t - 1*	-1.490*	-0.703***	-0.539***	-0.284***	0.026
	(0.836)	(0.101)	(0.094)	(0.076)	(0.127)
Total CHMA Land Acres (1,000s)	-0.004***	0.002*	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CHMA Border to Area Ratio	-5.637***	0.286	4.073***	-0.327	-0.835
	(0.845)	(1.005)	(0.830)	(0.870)	(1.525)
Average Parcel Acres	-0.038***	-0.028***	-0.084***	-0.0806***	-0.122***
	(0.010)	(0.008)	(0.008)	(0.010)	(0.015)
Controls for Cycle	Yes	Yes	Yes	Yes	Yes
Constant	5.501***	1.995**	4.231	2.046***	4.396***
	(0.609)	(0.841)	(0.885)	(0.753)	(1.119)
Rho	0.017	0.136	0.480***	0.224***	0.059
Lambda	-0.045	-0.002	-0.333***	-0.260***	0.080
Sigma	3.168***	3.059***	3.358***	3.603***	5.241***
N	846	799	846	799	799
LR Test (Rho = 0)	0.098	1.116	63.726***	9.577***	1.015
LR Test (Lambda = 0)	0.426	0.0001	11.065***	8.643***	1.346
LR Test SAC vs. OLS (Rho + Lambda = 0)	0.509	15.991***	126.358***	9.694***	11.421***
Wald Test	880.111***	1014.575***	1428.715***	1248.370***	1283.080***
Number Censored	5	5	4	16	15

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Robust standard errors in parentheses

Table 5. Spatial Tobit Model of the 75th Percentile of Psyllid Counts at the CHMA-Level by Count Cycle

75th Percentile	2012	2013	2014	2015	2016
Survey Respondent (SR)	2.503***	1.395*	6.009***	2.173*	3.346*
	(0.707)	(0.736)	(1.116)	(1.198)	(1.993)
SR x Currently Coordinating	-3.149***	1.087	-2.218*	-0.189	-0.681
	(0.802)	(0.998)	(1.332)	(0.912)	(1.951)
SR x Currently Coordinating x Years of Coordination	2.932	-0.999***	-0.425	-0.606	-0.475
	(0.359)	(0.583)	(0.419)	(0.477)	(0.477)
SR x Participation Rate, *t - 1*	-0.028	0.003	0.040	0.062*	-0.001
	(0.027)	(0.012)	(0.028)	(0.022)	(0.027)
SR x Number of Coordinated Applications, *t - 1*	-3.720**	-0.616***	-0.663***	-0.486***	-0.070
	(1.832)	(0.139)	(0.174)	(0.141)	(0.242)
Total CHMA Land Acres (1,000)	0.006***	-0.001	0.002*	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
CHMA Border to Area Ratio	-9.340***	0.555	4.916***	-0.830	-3.602
	(1.703)	(1.926)	(1.707)	(1.841)	(2.966)
Average Parcel Acres	-0.101***	-0.004	-0.051***	-0.043**	-0.140***
	(0.022)	(0.016)	(0.018)	(0.019)	(0.031)
Controls for Cycle	Yes	Yes	Yes	Yes	Yes
Constant	5.007***	7.527***	6.798***	12.809***	9.819***
	(1.211)	(1.362)	(1.683)	(2.640)	(2.060)
Rho	-0.009	-0.008	0.216***	-0.004	-0.043
Lambda	-0.052	0.039	-0.047	0.001	0.134*
Sigma	-5.911***	4.843***	5.759***	6.672***	9.634***
N	846	799	846	799	799
LR Test (Rho = 0)	0.059	0.049	160.067***	0.002	0.53
LR Test (Lambda = 0)	1.165	0.593	0.399	0.0001	3.583*
LR Test SAC vs. OLS (Rho + Lambda = 0)	1.636	0.633	30.966***	0.014	5.456*
Wald Test	672.157***	825.546***	1179.787***	875.287***	962.132***
Number Censored	201	205	221	163	93

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Robust standard errors in parentheses.