Heterogeneous Effects of Regulation: A Nonparametric Model of Residential Land Development

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- Recent decades have witnessed a significant increase in the extent of this type of development beyond the urban center (Brown et al., 2005; Irwin and Bockstael, 2007; Nechyba and Walsh, 2004).
- While most research has focused on demand, there has been an increase in interest in the importance of supply side factors in influencing housing and land markets(DiPasquale, 1999), including the role of increased regulation (Glaeser, Gyourko, and Saks, 2005; Murphy, 2010; Ortalo-Magne and Prat, 2007; Quigley and Raphael, 2005).

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Question 1

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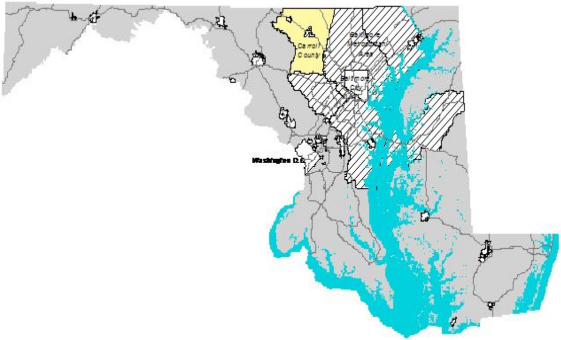
Question 1

Do land use regulations affect the likelihood of development?

Question 2

Is the effect of regulation heterogeneous across a spatially differentiated suburban-exurban landscape?

Study Region: Carroll County, Maryland



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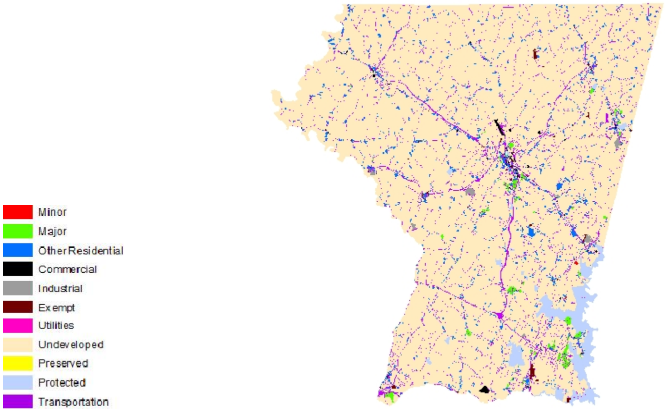
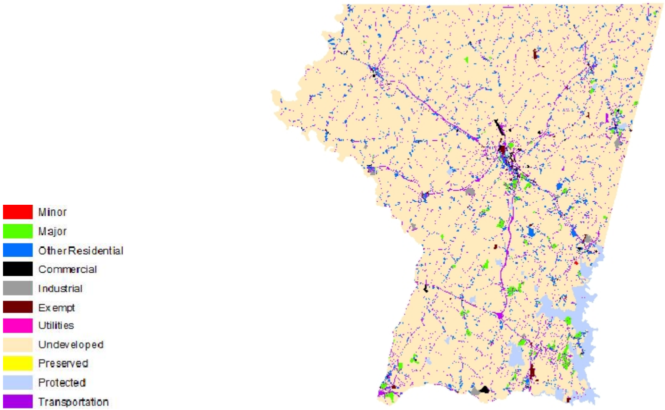
- In 1978 the county passed a second extensive land use plan that created a regulatory division between major and minor subdivision developments and the official subdivision regulation process in the county.

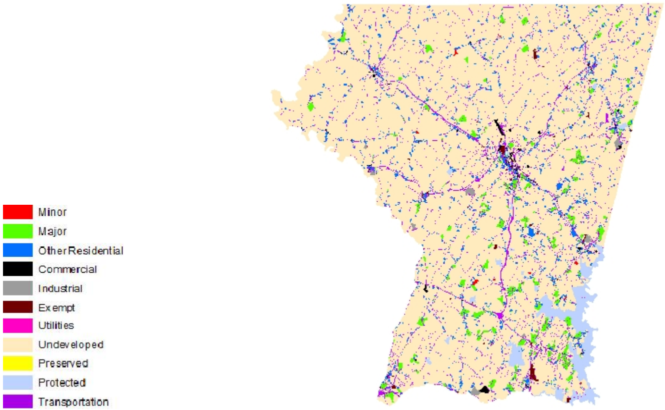
Carroll County Land Use 1960



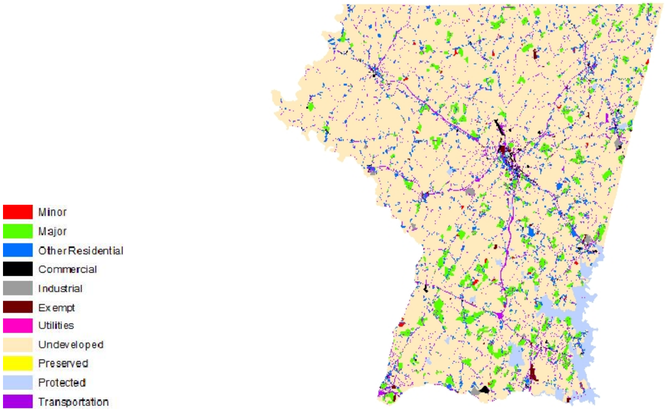
Carroll County Land Use 1965



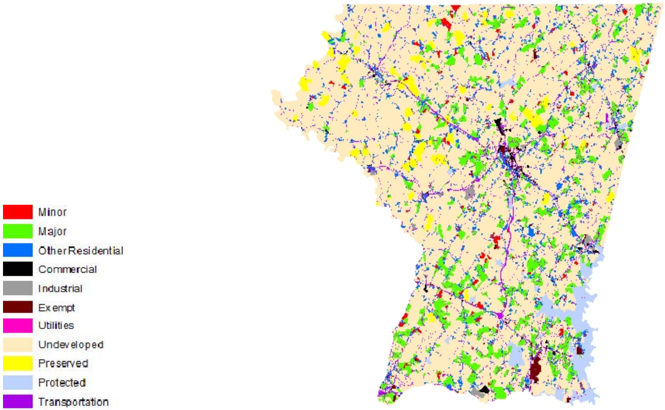
Carroll County Land Use 1970



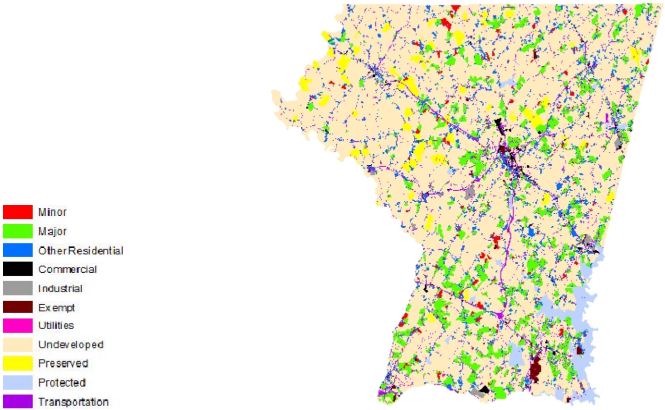
Carroll County Land Use 1975



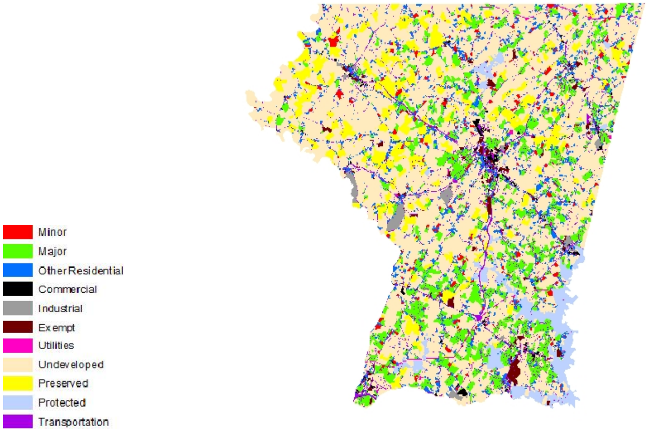
Carroll County Land Use 1980



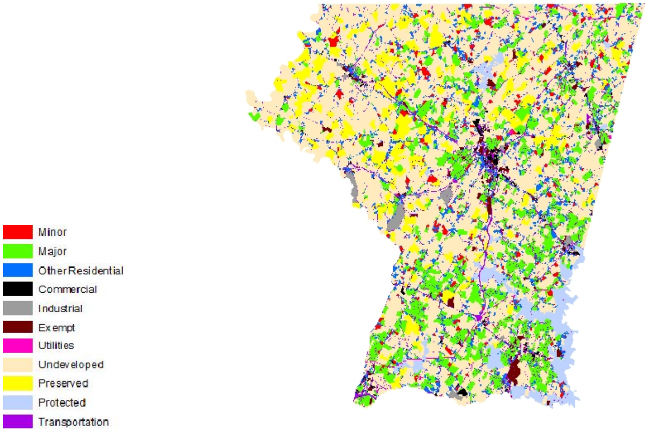
Carroll County Land Use 1985



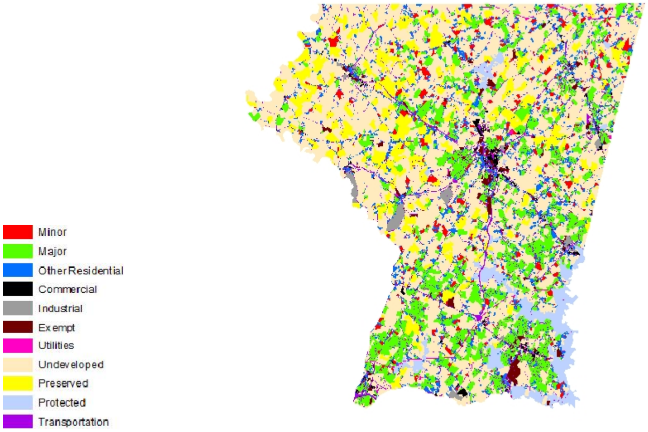
Carroll County Land Use 1990



Carroll County Land Use 1993



Carroll County Land Use 1996



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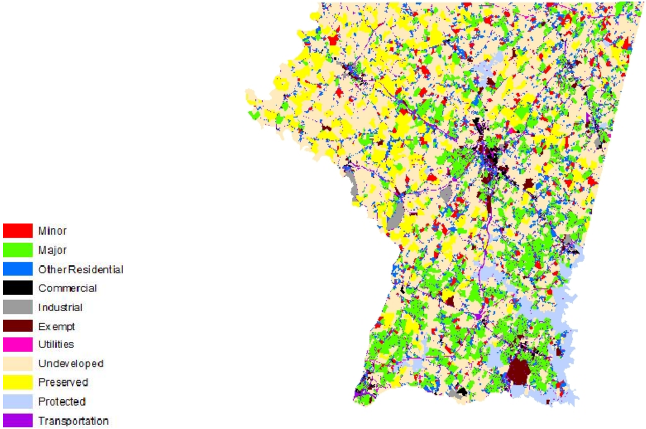
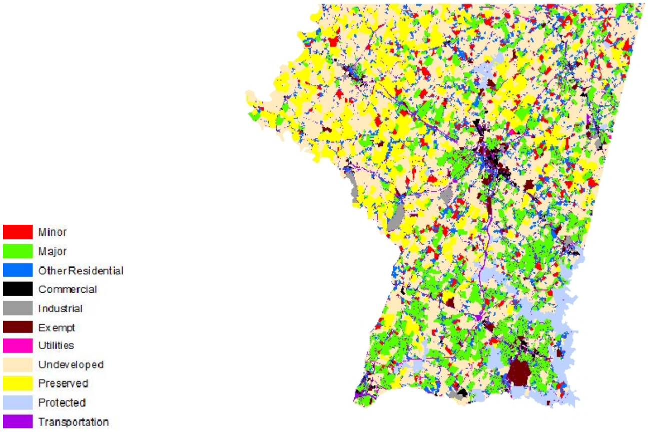
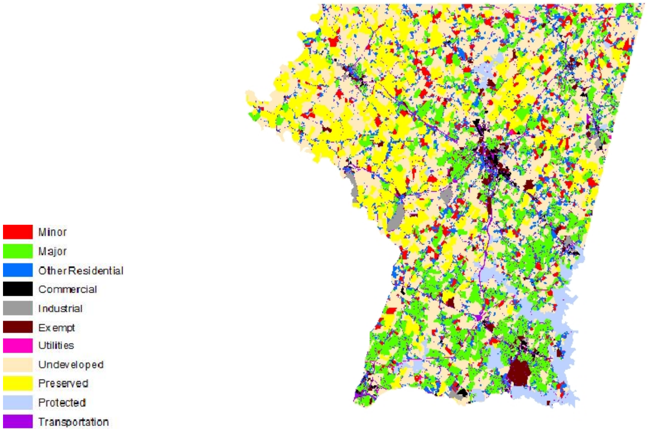


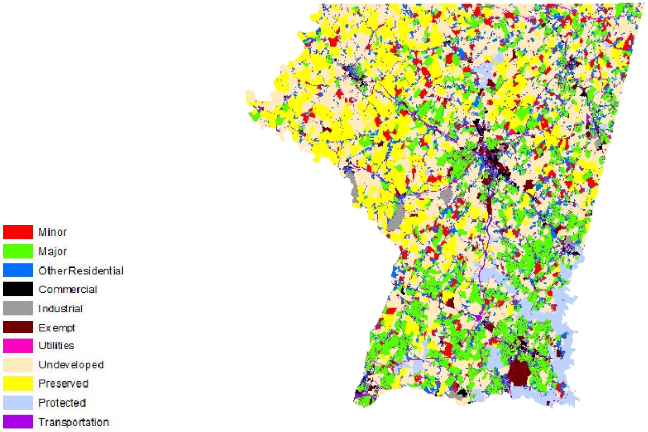
Carroll County Land Use 2002



Carroll County Land Use 2005



Carroll County Land Use 2007



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- Input Cost Uncertainty: Once a person decides to exercise her invest put option the project takes time to complete with the amount of investment in each period, $I(t)$, determined by $0 \leq I(t) \leq k$.
- The effect of regulatory uncertainty, ζ, is to make the final completion time of the project, $\tilde{T}$, uncertain from the perspective of the landowner at the time she starts the project.

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- Given that subdivision development takes time to complete, each landowner is assumed to form a prediction of expected completion time in each period based on past subdivision approval times.

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- Beck, Katz, and Tucker (1998) show that in the case of discrete-time binary time-series cross-section data a binomial model with logit link and time fixed effects is equivalent to a continuous-time proportional hazard model.

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where P_{nt} is equal to $\frac{exp(X_{nt}\beta+C_{nt}\alpha+\kappa_{t-t0})}{1+exp(X_{nt}\beta+C_{nt}\alpha+\kappa_{t-t0})}$ and K_n, which is the kernel weight for observation n, is equal to $K\left(\frac{Z_n-Z}{h}\right)$.

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- We estimate our current model at both the 40% window and 60% window and compare the estimates with those produced by the "global" discrete-time duration model.

Data Construction

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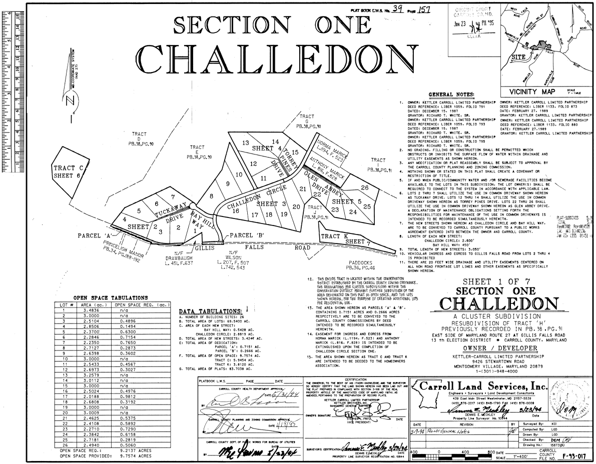
- A panel data set on residential subdivision approval timing in the county from 1989-2007. This was constructed by matching monthly zoning board data on approvals of subdivisions with our first data set of final subdivision approval gained from the subdivision plat maps.

Data Creation: Subdivision Plat Example



Construction of Regulatory Uncertainty Variable

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- To construct our measure of regulatory uncertainty for each parcel in each time period we estimate a two-step conditional survival model in each period and use the estimates from the second stage of the model to predict the expected completion times for each undeveloped parcel in that time period (Prentice, Williams, and Peterson, 1981).

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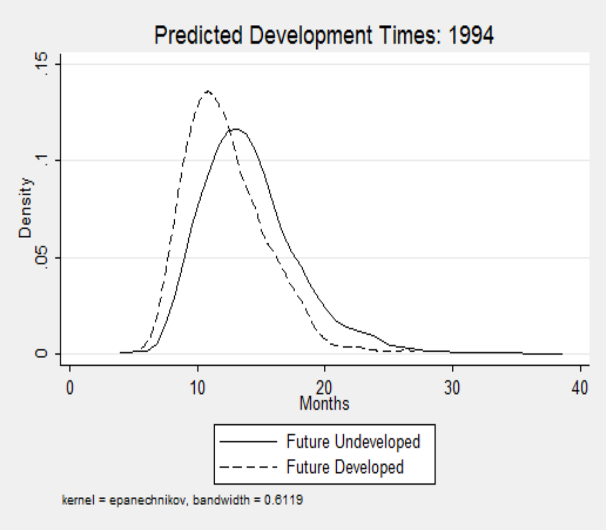
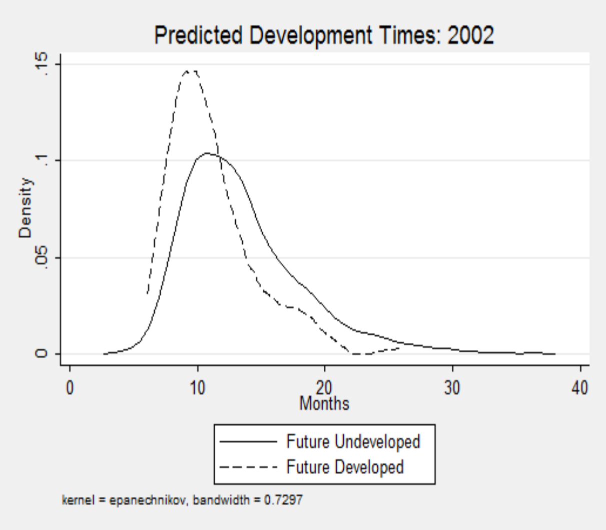
$$L(\beta_k) = \prod_{i=1}^{N} \prod_{k=1}^{2} h_{ik}((t_{ik1} - t_{ik0}), \beta_{ik})^{d_{ik}} S_{ik}((t_{ik1} - t_{ik0}), \beta_{ik})^{1-d_{ik}} \tag{5}$$

where k signifies the stage of the model.

Predicted Development Times: 1994



Predicted Development Times: 2002



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- Our data sample consists of all undeveloped and developed parcels in the county from 1995-2007.
- The final data set contains 46,143 parcel-time observations during this time period on 3,852 parcels. During this time period 410 parcels filed and gained conditional subdivision approval.

Results of Discrete Survival Models: Non-Regulatory Factors

	Nonparametric 40% Window				Nonparametric 60% Window				Global Discrete Survival	
	Coef.	Std. Dev.	Min.	Max.	Coef.	Std. Dev.	Min.	Max.	Coef.	Std. Err.
Intercept	-4.615	1.702	-8.690	-0.488	-4.416	1.064	-6.592	-2.229	-4.837	0.980
Non-Regulatory Factors										
Balt. City	-0.007	0.014	-0.052	0.028	-0.011	0.007	-0.025	0.001	-0.016	0.011
SluTran	0.019	0.020	-0.020	0.076	0.013	0.014	-0.010	0.045	0.011	0.014
SluSubdiv	0.029	0.010	0.008	0.043	0.028	0.008	0.014	0.039	0.029	0.003
SluRes	0.026	0.012	0.000	0.052	0.025	0.008	0.009	0.045	0.026	0.005
SluUDR	-0.044	0.009	-0.062	-0.018	-0.044	0.006	-0.056	-0.030	-0.046	0.004
SluPre	0.007	0.013	-0.025	0.026	0.007	0.008	-0.009	0.017	0.006	0.005
SluPro	-0.250	0.482	-2.833	0.026	-0.037	0.053	-0.241	0.018	0.001	0.014
SluComm	-0.017	0.028	-0.076	0.029	-0.017	0.020	-0.057	0.012	-0.018	0.010
SluInd	-0.006	0.026	-0.077	0.033	-0.007	0.015	-0.043	0.021	0.000	0.016
Area	0.020	0.007	0.006	0.046	0.019	0.003	0.012	0.029	0.017	0.004
AreaSqrd	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Zoned Lt. Yield	0.004	0.003	-0.001	0.009	0.003	0.001	0.000	0.006	0.004	0.001
Exhouse	0.561	0.426	-0.333	1.494	0.509	0.285	0.028	1.116	0.501	0.117
Sewer	0.592	0.464	-0.419	1.397	0.579	0.330	-0.153	1.083	0.408	0.284
Ag. Zoning	0.815	0.528	-0.120	1.657	0.749	0.375	0.156	1.302	0.775	0.156
Type 1 Soil	-0.001	0.010	-0.020	0.022	-0.001	0.007	-0.015	0.012	-0.001	0.004
Type 2 Soil	-0.002	0.009	-0.022	0.017	-0.002	0.006	-0.016	0.008	-0.001	0.004
Slope	-0.003	0.003	-0.009	0.005	-0.003	0.002	-0.006	0.001	-0.002	0.003
Forest Cover	0.006	0.007	-0.007	0.023	0.006	0.005	-0.002	0.017	0.007	0.004
Competition	-0.006	0.003	-0.012	-0.001	-0.005	0.001	-0.007	-0.003	-0.005	0.003
Drift	0.023	0.161	-0.335	0.349	0.012	0.103	-0.218	0.247	0.019	0.069
Volatility	0.095	0.190	-0.405	0.520	0.121	0.097	-0.114	0.359	0.192	0.078

Note: Nonparametric models show standard deviations and ranges of coefficients.

Note: Parametric models show 5% level in red and 10% in blue.

N=46143

Results of Discrete Survival Models: Regulatory Factors

	Nonparametric 40% Window				Nonparametric 60% Window				Global Discrete Survival	
	Coef.	Std. Dev.	Min.	Max.	Coef.	Std. Dev.	Min.	Max.	Coef.	Std. Err.
Regulatory Factors										
Reg. Costs	-0.219	0.086	-0.443	-0.083	-0.222	0.055	-0.353	-0.139	-0.211	0.056
Log-Likelihood	-1852.267				-1923.964				-2086.456	

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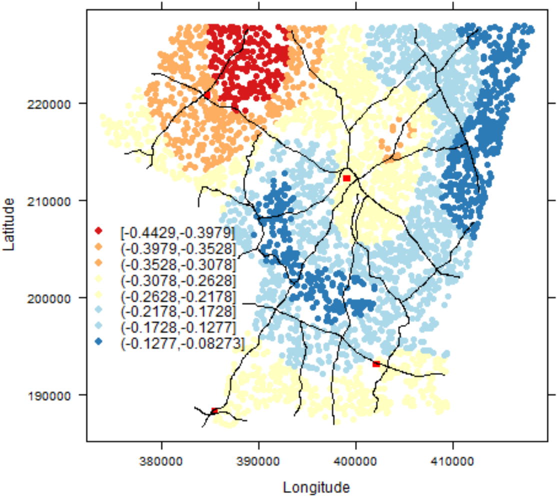
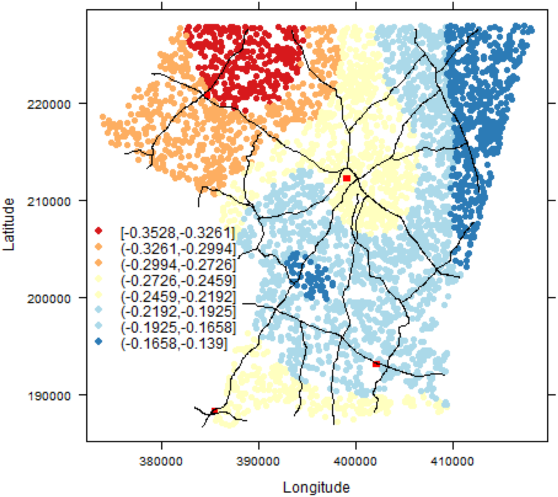
Regulatory Costs: 40% Window Size



Regulatory Costs: 60% Window Size



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- These results are consistent with the scattered development pattern and increases in smaller developments outside of areas with public services.
- These findings are important from a policy perspective in that they suggest that the areas most likely to develop are those that were supposed to be the most heavily regulated. Officials could use this result to try and reduce regulations on developers willing to build in areas with public services.

Thank You

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