The Grass is Not Always Greener: Peer Effects in Dry Landscape Adoption

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Motivation

- Can we explain dry landscape adoption decisions through peer effects?
- If so, to what extent can a model of social influence help with:
  - Explaining water use patterns
  - Forecasting water use
  - Affecting conservation behavior (social spillovers)

Evidence on Peer Effects in Many Settings

Extensive work on social interaction effects influencing decisions:

- Education - Hoxby (2000), Sacerdote (2001), Cipollone & Pellizzari (2007), Duflo et al. (2008), Ammermueller & Pischke (2009), De Giorgi et al. (2010).
- Criminal activity - Glaeser et al. (1996).
- Retirement plans - Duflo & Saez (2003).
- Welfare participation - Bertrand et al. (2000).
- Agricultural technology adoption - Foster & Rosenzweig (1995), Conley & Udry (2010).

Work on Peer Influence in Environmental Decisions

- Kahn & Vaughn (2009) - Hybrids and LEED buildings exhibit clustering behavior.
- Narayanan and Nair (2011) - Causal installed-base effects in Prius adoption.
- Allcott (2010) - Reducing electricity use in response to information on peers.
- Ferraro & Price (2013) - Norm-based messages reduce water usage.
- Bollinger & Gillingham (2012), Graziano and Gillingham (2014) - Peer effects in solar PV adoption.

Challenges for Identifying Peer Effects

1. Simultaneity - I affect my peers just as they affect me.
2. Endogenous Group Formation (homophily)- People self-select into groups of peers.
3. Correlated Unobservables - Other factors that affect neighbors at the same time.

Our strategy: Use movers as an instrument for landscape changes, with neighborhood and time fixed effects.

Linear-in-Means Model

The model:

$$y_i = \alpha + \beta x_i + \gamma w_g + \theta \mathbb{E}\left[y_g\right] + \delta m_i + \epsilon_i$$

Note that:

$$\mathbb{E}\left[y_g\right] = \frac{\left(\alpha + \beta \overline{x}_i + \gamma w_g + \delta \overline{m_i}\right)}{1 - \theta}$$

Therefore we can use $\overline{m_i}$ as an instrument for the adoption decision of peers.

Homophily and Correlated Unobservables

- Problems of homophily and correlated unobservables can still be present.
- We combat these issues with group fixed effects (which also absorb the mean group characteristics) and time dummies.
- Our instrumentation strategy further alleviates the concern since we would expect the correlated dry landscape adoption shocks to be unrelated to moving decisions.
- We present results with levels and differences.

Data Sources

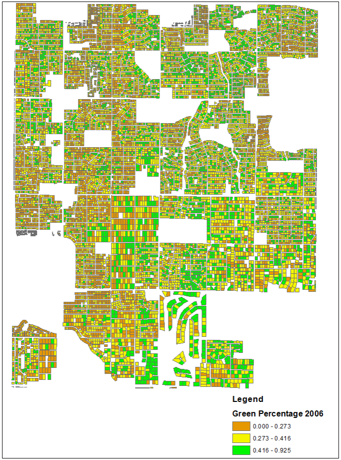
- Housing Characteristics (Assessor)
- Detailed household level demographic variables (Acxiom)
- Remote sensing classification data on parcel land use (City of Phoenix)

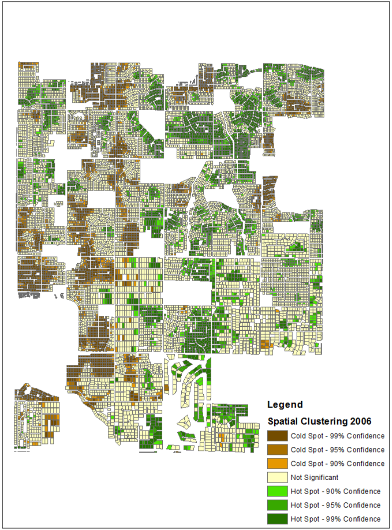
Housing and Demographic Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	N
bathroom fixtures	7.22	2.413	2	40	427,758
livable area (sq ft)	1851	671.344	322	15449	427,758
year built	1974	15.147	1900	2012	427,758
pool size (sq ft)	450	95.452	52	2009	187,590
project	0.682	0.466	0	1	429,156
number of kids	0.505	0.816	0	6	403,284
income (1,000's)	155.615	169.137	15	500	403,284
age	56.9	14.749	18	99	307,147
home value (1,000's)	368.079	751.717	25	10000	399,346

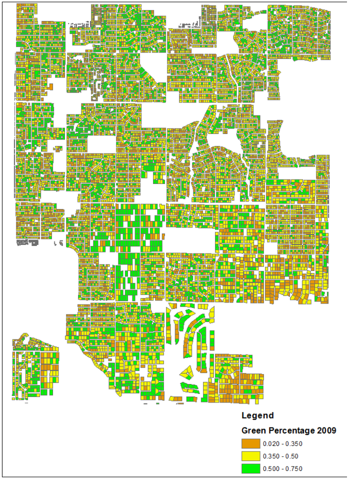
Parcel Coding Example

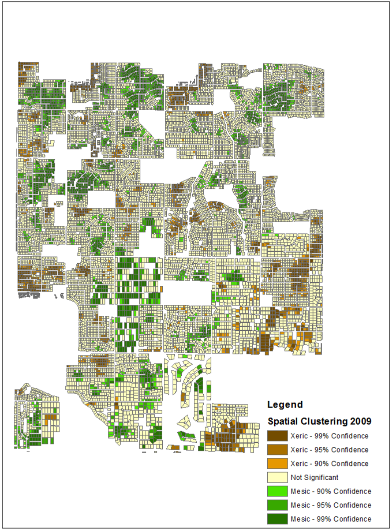
2006 Parcel Vegetation



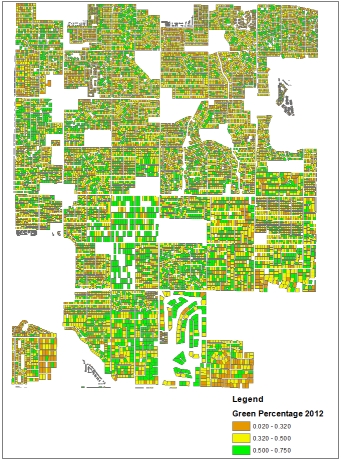


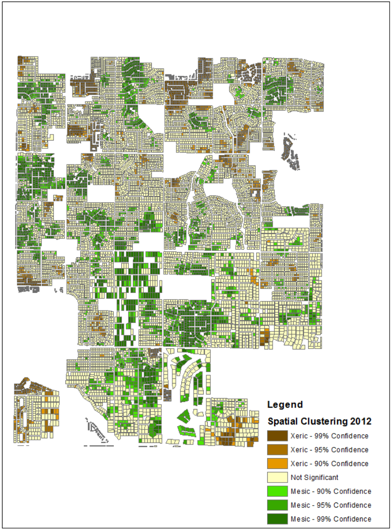
2009 Parcel Vegetation



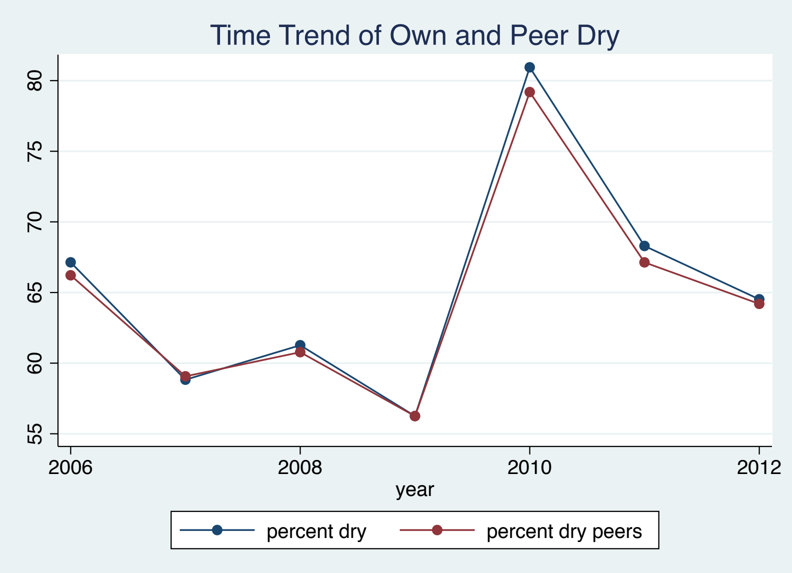


2012 Parcel Vegetation

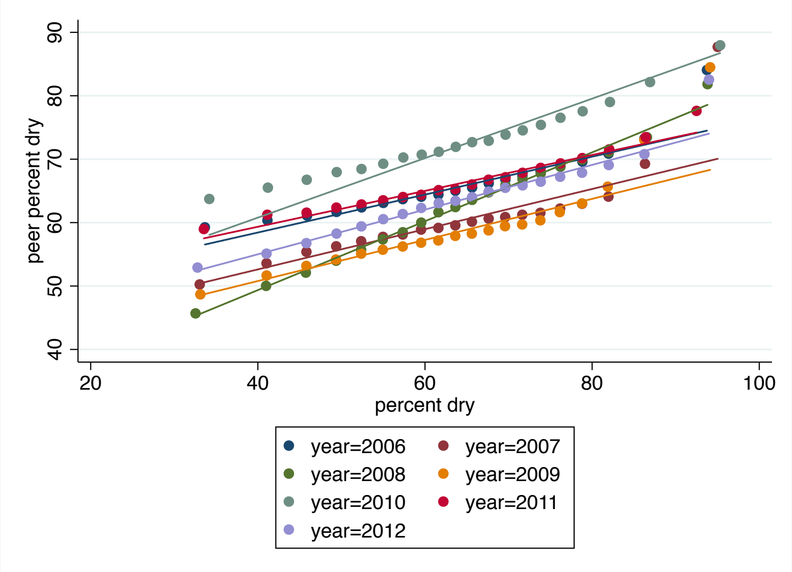




Vegetation over Time



Correlation in Vegetation with Peers



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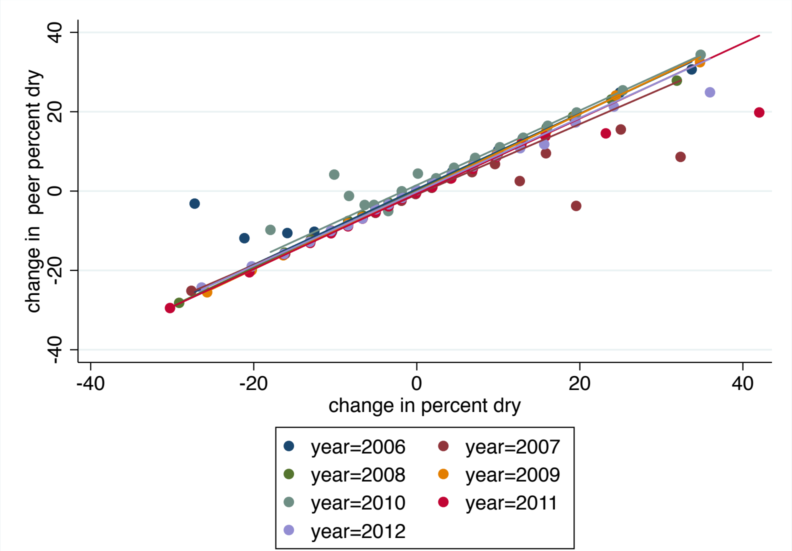

Peer Effect Regressions

	OLS levels	IV levels	OLS differences	IV differences
peer (200m)	0.861***	0.473*	0.951***	0.989***
	(0.005)	(0.195)	(0.002)	(0.051)
Year FE	Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y
R-squared	0.416	0.382	0.694	0.693
N	426591	426577	424893	424870

s.e. clustered on neighborhood in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Peer Effect Regressions with Different Radii

	OLS levels	IV levels	OLS differences	IV differences
peer (200m)	0.683***	0.425	0.767***	1.187***
	(0.012)	(0.310)	(0.010)	(0.283)
peer (400m)	0.233***	-0.085	0.191***	0.110
	(0.013)	(0.257)	(0.011)	(0.302)
peer (600m)	0.027**	0.691	0.021***	-0.298
	(0.008)	(0.413)	(0.006)	(0.290)
Year FE	Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y
R-squared	0.424	0.376	0.699	0.685
N	344884	344880	344135	344132

s.e. clustered on neighborhood in parentheses

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Peer Effect Regressions with Demographics

	OLS levels	IV levels	OLS differences	IV differences
peer (200m)	0.841***	0.540***	0.961***	1.259***
	(0.011)	(0.119)	(0.007)	(0.138)
peer x income	0.181*	1.089	0.022	-0.081
	(0.075)	(0.728)	(0.050)	(1.126)
peer x age	-0.031*	0.353**	-0.018	-0.287
	(0.014)	(0.130)	(0.010)	(0.199)
peer x home value	-0.016	-0.668	-0.107**	-0.721
	(0.064)	(0.649)	(0.040)	(0.831)
peer x number kids	0.379	2.368	0.354*	-3.197
	(0.249)	(2.224)	(0.179)	(3.484)
peer x project	3.832***	13.743*	1.042***	-0.454
	(0.461)	(6.485)	(0.255)	(4.389)
income	-0.049	0.278	-0.015***	-0.013
	(0.028)	(0.261)	(0.003)	(0.010)
age	-0.025***	0.112*	-0.001	0.002
	(0.005)	(0.046)	(0.001)	(0.002)
home value	0.071*	-0.166	0.017***	0.023**
	(0.031)	(0.233)	(0.005)	(0.009)
number kids	-0.033	0.674	-0.023*	0.008
	(0.094)	(0.799)	(0.011)	(0.031)
project	0.859*	4.568	-0.205**	-0.185
	(0.343)	(2.470)	(0.077)	(0.096)

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- Thank you!