Progress Update

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Updates

1. Background
2. Paper Recommendation (Yuanning Liang,2021)
3. Current Results of Event Study Model
4. Next Steps (4 Zoning Types)

Background

Background

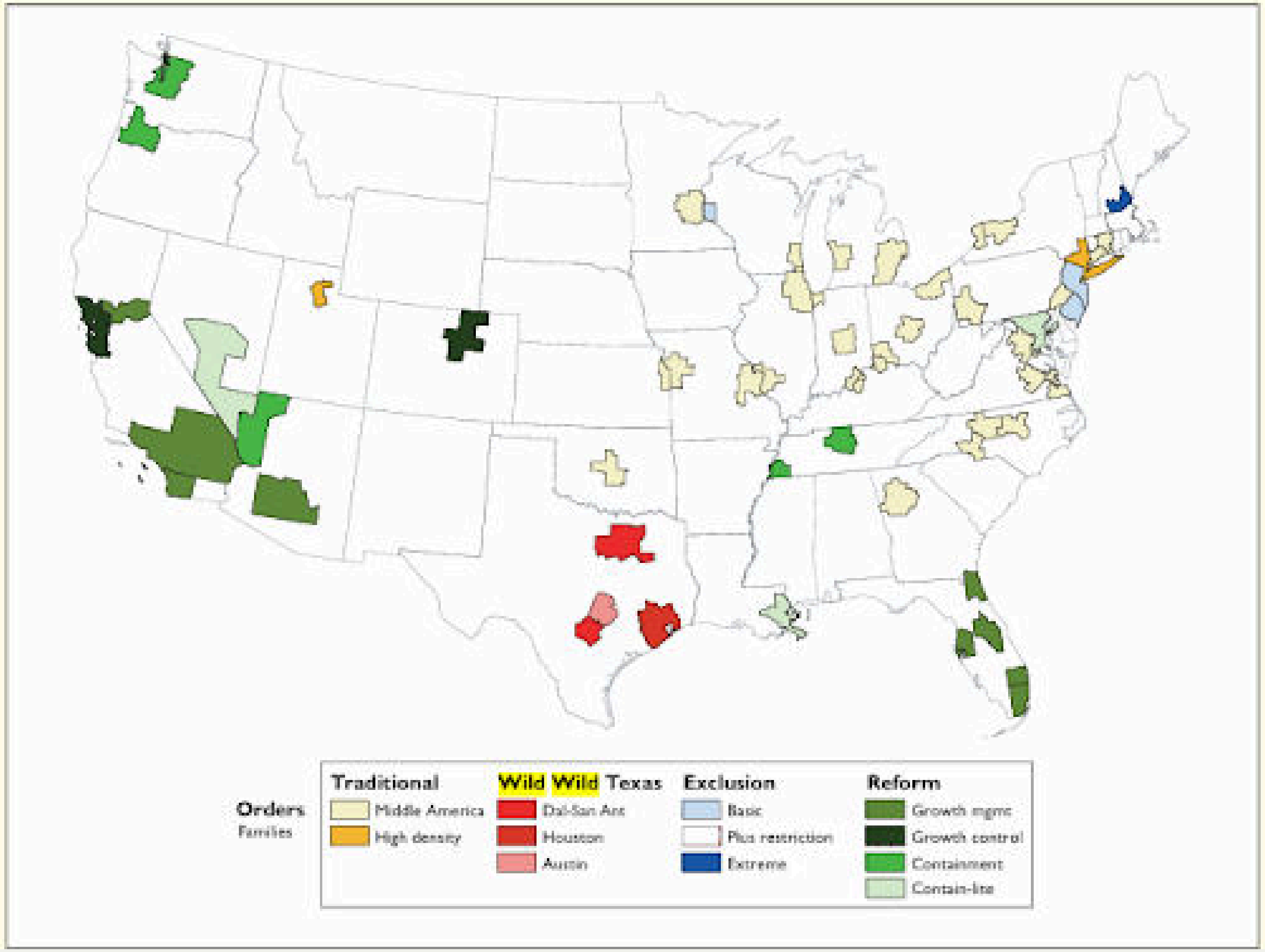
- 90,056 local governments
- Inadequate truck parking has led to dangerous or illegal practices (such as **parking on highway shoulders** or in unauthorized areas, which heightens traffic accident risks and imposes economic costs like increased fuel consumption, delivery delays, and inflated goods prices)
- limited empirical research
- traffic accident data as a proxy for truck parking demand -> land-use regulations -> truck parking availability.

Zoning regulation welfare-enhancing?

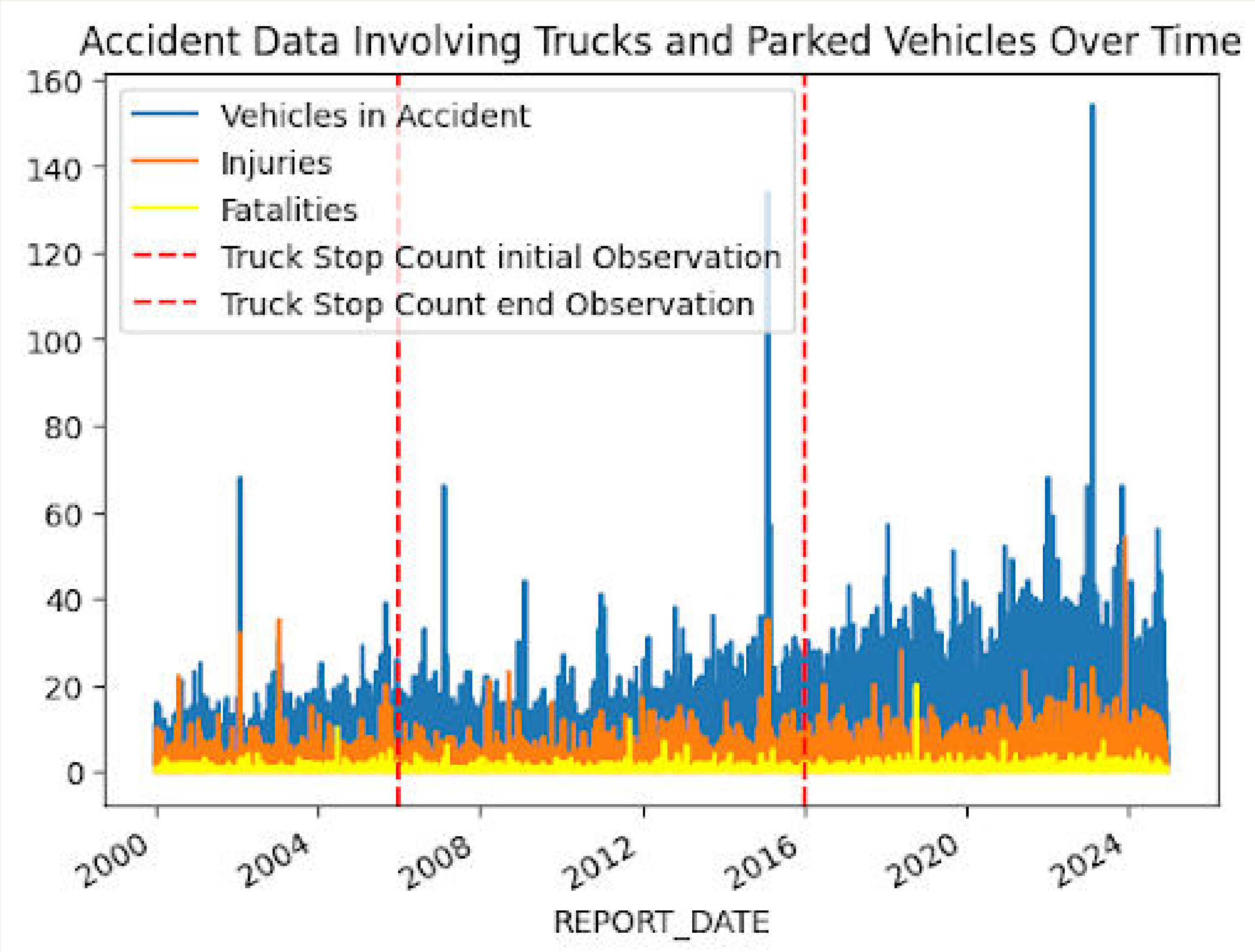
No Truck Parking → Trucks will illegally park → **Accidents Occur** (observed)→Truck Parking Demand increases → **Truck Parking Capacity Increase** (observed)

4 Zoning Categories

Map 7. Typology of Land Use Regulations, by metropolitan area (or part)



Data


Accident Data Involving Trucks and Parked Vehicles Over Time
Vehicles in Accident
Injuries
Fatalities
Truck Stop Count initial Observation
Truck Stop Count end Observation
160
140
120
100
80
60
40
20
0
2000
2004
2008
2012
2016
2020
2024
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Event Study Model

$$\Delta \text{NumTruckStop}_{tj} = \sum_{i=-n}^{n} \beta_{ij} \text{Accident}_{ij} \cdot \text{Severity}_{ij}$$
$$+ \gamma_{tj} X_{tj} + \epsilon_{tj}$$

year t ,category j, time i

- $\Delta \text{NumTruckStop}_{tj}$ —- change in truck stop
- $\text{Accident}_{i,j}$ -– event dummy indicating the presence of a Accident
- Severity_{ij} -– fatalities/injuries/vehicle associated

Adjusted Event Model

$$\Delta \text{NumTruckStop}_{j,t=2006-2016} =$$

$$\sum_{i=-2}^{0} \beta_{j,t+i} \text{Accident}_{j,t+i} \cdot \text{Severity}_{j,t+i} + \gamma_{tj} X_{tj} + \epsilon_{tj}$$

- year t ,category j, time i
- $\Delta\text{NumTruckStop}_{tj}$ —- change in truck stop
- $\text{Accident}_{i,j}$ –- event dummy: presence of a Accident
- Severity_{ij} –- fatalities/injuries/vehicle associated

(Yuanning Liang,2021)

- Useful and highly relevant data description

Adjusted Even Study Model Results

Fatalities Model

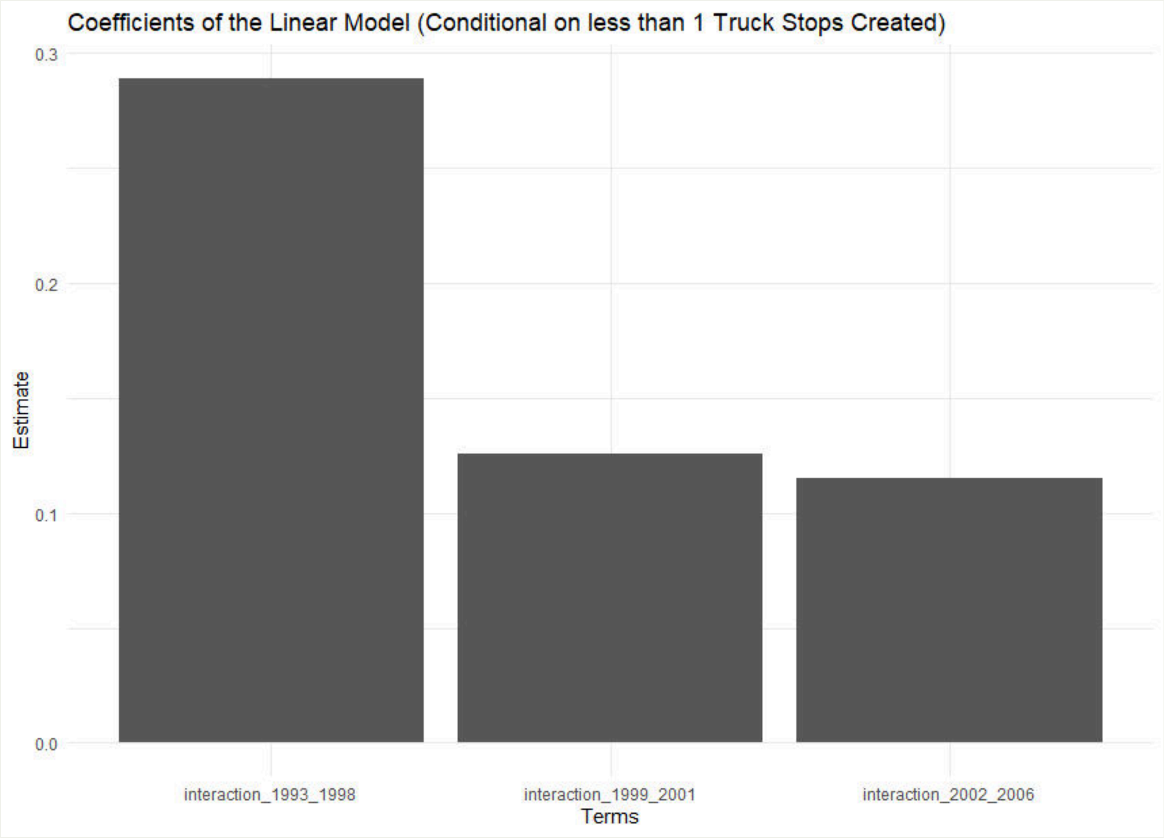
we see its mostly noise

Linear Model Summary

	Dependent variable:			
	change_2006_2016			
	Unconditioned	Conditional on More Than 2 Truck Stops Created	Conditional on More Than 1 Truck Stops Created	Conditional on less than 1 Truck Stops Created
	(1)	(2)	(3)	(4)
interaction_2002_2006	0.122	-0.267	0.075	0.115
	(0.142)	(0.225)	(0.166)	(0.133)
interaction_1999_2001	-0.078	-0.437	-0.279	0.126
	(0.168)	(0.384)	(0.244)	(0.146)
interaction_1993_1998	0.286^{*}	-0.192	0.078	0.289^{**}
	(0.162)	(0.339)	(0.227)	(0.141)
Constant	-0.273	3.361^{***}	1.648^{***}	-1.056^{***}
	(0.182)	(0.370)	(0.237)	(0.164)
Observations	366	34	105	261
R^2	0.016	0.065	0.030	0.016
Adjusted R^2	0.007	-0.029	0.002	0.005
Residual Std. Error	1.666 (df = 362)	1.144 (df = 30)	1.134 (df = 101)	1.267 (df = 257)
F Statistic	1.913 (df = 3; 362)	0.692 (df = 3; 30)	1.059 (df = 3; 101)	1.416 (df = 3; 257)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

No truck stop creation is related to higher accidents

high accidents -> less than 1 truck stop made



Injuries Model

mostly noise

Linear Model Summary				
	Dependent variable:			
	change_2006_2016			
	Unconditioned	Conditional on More Than 2 Truck Stops Created	Conditional on More Than 1 Truck Stops Created	Conditional on less than 1 Truck Stops Created
	(1)	(2)	(3)	(4)
interaction_2002_2006	0.072**	0.014	0.007	0.009
	(0.031)	(0.080)	(0.026)	(0.048)
interaction_1999_2001	-0.018	0.019	-0.038	0.003
	(0.048)	(0.161)	(0.083)	(0.043)
interaction_1993_1998	0.040	0.060	0.053	0.050
	(0.033)	(0.044)	(0.042)	(0.033)
Constant	-0.527***	3.017***	1.742***	-1.151***
	(0.151)	(0.386)	(0.193)	(0.162)
Observations	379	34	92	287
R^2	0.020	0.061	0.025	0.011
Adjusted R^2	0.012	-0.033	-0.008	0.001
Residual Std. Error	1.768 (df = 375)	1.203 (df = 30)	1.268 (df = 88)	1.303 (df = 283)
F Statistic	2.545* (df = 3; 375)	0.653 (df = 3; 30)	0.752 (df = 3; 88)	1.065 (df = 3; 283)
Note:				*p<0.1; **p<0.05; ***p<0.01

Vehicle Model

Conditioning on places with a high truck stop creation.

high accidents -> less truck stop creation

Linear Model Summary

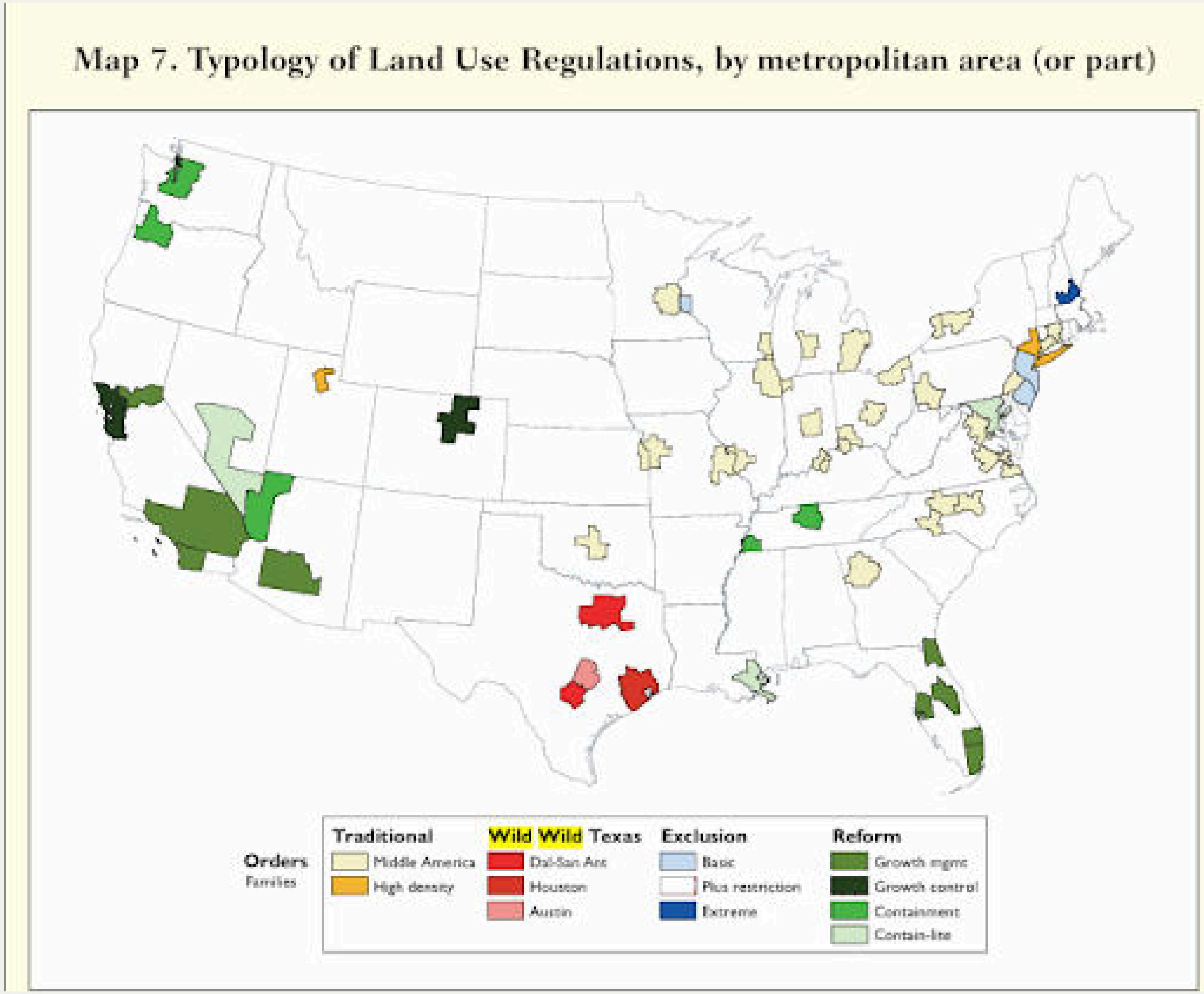
	Dependent variable:			
	change_2006_2016			
	Unconditioned	Conditional on More Than 2 Truck Stops Created	Conditional on More Than 1 Truck Stops Created	Conditional on less than 1 Truck Stops Created
	(1)	(2)	(3)	(4)
interaction_2002_2006	0.026	-0.163	-0.024	0.019
	(0.031)	(0.114)	(0.021)	(0.059)
interaction_1999_2001	0.020	-0.308*	-0.163**	0.047
	(0.063)	(0.165)	(0.069)	(0.073)
interaction_1993_1998	0.060	-0.023	-0.075	0.059
	(0.043)	(0.150)	(0.045)	(0.051)
Constant	-0.670**	4.106***	2.262***	-1.461***
	(0.259)	(0.774)	(0.273)	(0.365)
Observations	211	20	56	155
R^2	0.010	0.273	0.107	0.013
Adjusted R^2	-0.004	0.137	0.056	-0.007
Residual Std. Error	1.987 (df = 207)	1.139 (df = 16)	1.229 (df = 52)	1.550 (df = 151)
F Statistic	0.709 (df = 3; 207)	2.003 (df = 3; 16)	2.087 (df = 3; 52)	0.646 (df = 3; 151)
Note:				*p<0.1; **p<0.05; ***p<0.01

Conclusion and Next Steps

- We found evidence supporting that places with high truck stops creation don’t/negatively responds to accidents. This supports the idea that places do not respond to the need for truck stops.
- We will start categorizing zoning areas into the 4 types of zoning

Next Steps: 4 Categories

4 Categories (Map)



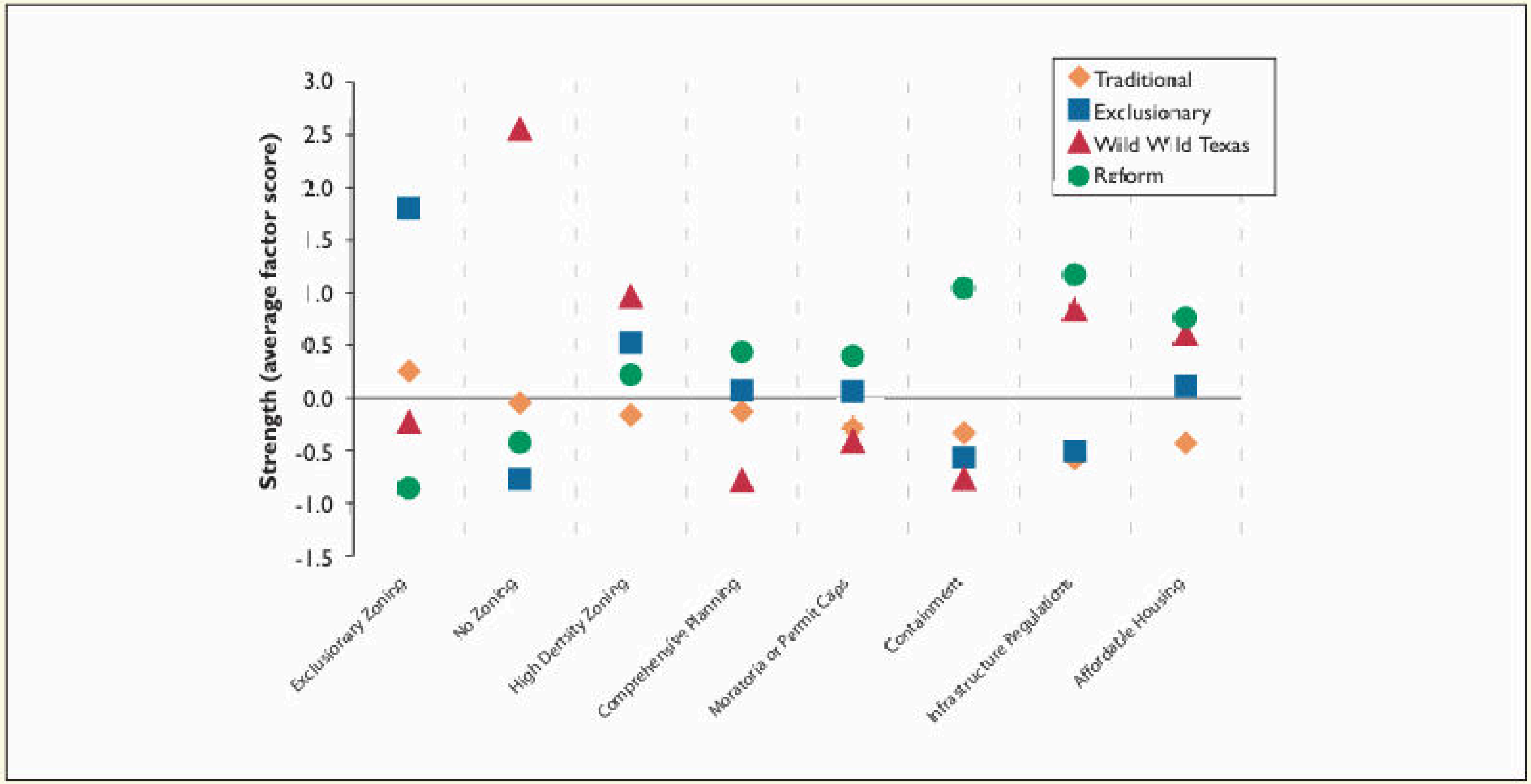
4 Categories (Summary Statistics)

Table 3. Typology of Land Use Regulations, by Orders and Families, Major U.S. Metropolitan Areas, 2003

Regulatory Orders and Families	Number of Metropolitan (or Sub-metropolitan) areas	Total Population
Traditional	34	75,483,321
Middle America	32	61,459,742
High Density	2	14,023,579
Exclusion	5	14,621,514
Basic Exclusion	3	8,563,688
Exclusion with Restriction	1	5,287,393
Extreme Exclusion	1	770,433
Wild Wild Texas	4	12,733,518
Austin	1	1,249,763
Houston	1	4,669,571
Dallas/San Antonio	2	6,814,184
Reform	19	59,340,464
Containment	5	7,838,637
Containment-Lite	3	7,496,135
Growth Management	9	34,384,824
Growth Control	2	9,620,868

4 Categories (Properties)

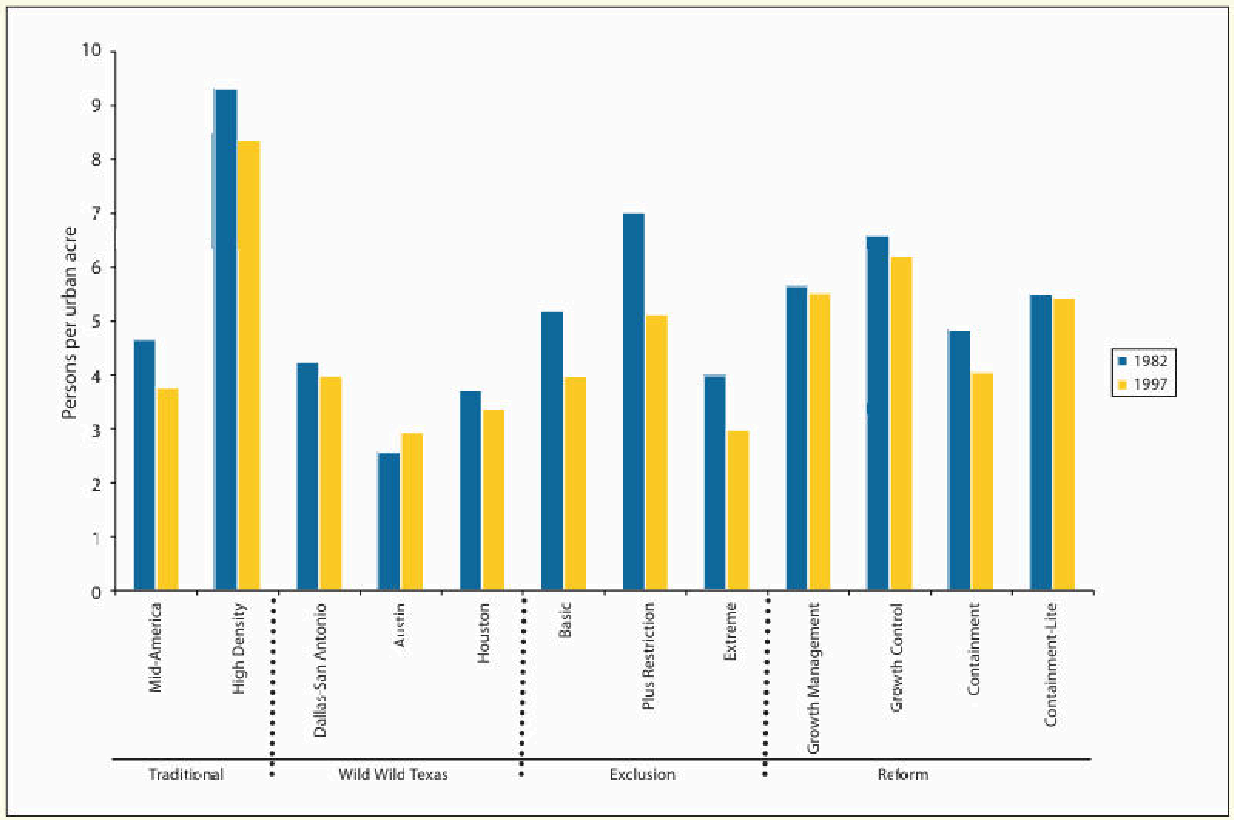
Figure 7. Regulatory Orders by Strength of Land Use Tool



4 Categories

Places exhibit properties we expect and are Stable and Consistent

Figure 8. Density (persons per urban acre), Regulatory Families, 1982 and 1997



Data Encoding (work in progress)

Zoning types will be incorporated into event study model

Appendix. Results of Factor Analysis, by metropolitan area (or part) and rank.

Metropolitan area or part	Region	Family	Zoning: Exclusion	Zoning: No Zoning	Zoning: Planning	Containment	Infrastructure: Impact Fee	Infrastructure: APFO	Growth Control: Moratoria	Growth Control: Permit Cap	Affordable Housing
Atlanta	S	Middle America	0.35 (28)	-0.35 (45)	0.49 (42)	-0.99 (65)	-0.75 (52)	-0.11 (45)	0.29 (43)	-0.39 (59)	-0.78 (57)
Austin	S	Austin	-0.57(52)	2.21(3)	-1.82 (71)	-0.66 (49)	0.69 (19)	-1.43 (69)	0.39 (35)	-0.35 (56)	0.93 (13)
Boston (MA)	NE	Exclusion with Restriction	1.19 (8)	-0.68 (64)	-1.08 (65)	-0.79 (56)	-1.09 (68)	0.00 (39)	-0.73 (66)	3.17 (2)	0.74 (17)
Boston (NH)	NE	Extreme Exclusion	2.12 (3)	-1.08 (70)	0.67 (1)	-0.40 (37)	-0.07 (32)	-0.37 (52)	-0.51 (61)	3.01 (3)	-0.48 (46)
Buffalo	NE	Middle America	0.65 (18)	-0.51(53)	-0.32 (50)	-0.99 (64)	-0.53 (47)	0.08 (32)	0.35 (41)	0.35 (14)	-0.32 (38)
Charlotte (NC)	S	Middle America	-0.55 (51)	-0.3 (42)	0.16 (44)	-0.29 (34)	-0.62 (49)	0.76 (11)	0.07 (56)	-0.02 (20)	0.42 (21)
Charlotte (SC)	S	*	-0.41 (41)	0.49 (12)	0.67 (1)	-1.05 (66)	0.46 (25)	-2.67 (72)	0.58 (1)	-0.27 (29)	-1.25 (69)
Chicago (IL)	MW	Middle America	0.42 (25)	0.86 (9)	-1.26 (66)	-0.60 (45)	0.05 (29)	-0.97 (65)	0.55 (17)	-0.19 (24)	-0.47 (44)
Chicago (IN)	MW	Middle America	0.38 (26)	-0.34 (44)	0.67 (1)	0.07 (28)	-1.08 (66)	-0.02 (40)	0.50 (21)	-0.05 (21)	-0.47 (45)
Chicago (WI)	MW	Middle America	0.38 (27)	-0.17 (31)	-0.18 (45)	0.47 (22)	-0.31 (38)	-1.36 (68)	0.37 (37)	0.12 (18)	-1.02 (61)
Cincinnati (IN)	MW	*	0.55 (20)	-0.24 (35)	0.67 (1)	-0.89 (62)	-1.09 (67)	0.03 (38)	0.27 (45)	0.61 (11)	-1.18 (67)
Cincinnati (KY)	S	Middle America	-0.41 (45)	0.27 (17)	0.67 (1)	0.69 (17)	-0.29 (37)	2.49 (2)	0.58 (1)	-0.27 (29)	-0.56 (51)
Cincinnati (OH)	MW	Middle America	0.87 (12)	0.70 (10)	-0.64 (59)	-0.46 (40)	-1.02 (60)	0.31 (22)	0.18 (48)	-0.44 (61)	-0.69 (53)
Cleveland	MW	Middle America	0.78 (14)	0.86 (8)	-0.60 (57)	-0.74 (50)	-0.79 (55)	0.07 (33)	0.19 (47)	-0.29 (43)	-0.41 (42)
Columbus	MW	Middle America	0.90 (11)	0.60 (11)	-0.95 (62)	-0.78 (54)	-0.98 (59)	0.27 (24)	-0.50 (60)	-0.72 (69)	-0.31 (37)
Dallas	S	Dallas-San Antonio	-0.42 (46)	1.57 (6)	0.53 (39)	-0.62 (46)	1.04 (14)	-0.49 (55)	0.36 (39)	-0.37 (58)	-0.13 (33)
Denver	W	Growth Control	-1.10 (66)	-0.37 (46)	0.67 (1)	2.01 (5)	0.72 (18)	-0.65 (57)	-1.33 (68)	3.96 (1)	0.27 (27)
Detroit	MW	Middle America	0.49 (23)	-0.13 (28)	0.54 (38)	-0.41 (38)	-1.03 (61)	0.16 (30)	0.47 (25)	-0.31 (47)	-0.73 (55)
Grand Rapids	MW	Middle America	0.76 (15)	-0.10 (27)	0.49 (41)	-0.53 (42)	-1.05 (62)	0.10 (31)	0.39 (34)	-0.35 (55)	-1.04 (62)
Greensboro	S	Middle America	-0.40 (40)	-0.21 (33)	-0.23 (48)	0.10 (27)	-0.79 (54)	0.64 (13)	0.51 (19)	-0.24 (26)	0.09 (31)
Hartford	NE	Middle America	1.51 (5)	-0.58 (58)	0.65 (34)	-0.80 (58)	-1.07 (65)	0.39 (19)	0.14 (49)	-0.46 (62)	-0.34 (39)
Houston	S	Houston	0.72 (17)	4.71 (1)	-2.55 (72)	-1.05 (66)	0.61 (21)	0.26 (26)	0.58 (1)	-0.27 (29)	0.42 (22)
Indianapolis	MW	Middle America	-0.17 (35)	-0.27 (36)	0.67 (1)	-0.94 (63)	-1.10 (69)	0.04 (36)	0.21 (46)	0.72 (10)	-0.66 (52)
Jacksonville	S	Growth Management	-1.00 (63)	-0.30 (39)	0.67 (1)	-0.04 (31)	1.64 (6)	2.75 (1)	-0.13 (58)	-0.57 (67)	1.56 (6)
Kansas City (KS)	MW	Middle America	-0.50 (49)	-0.68 (65)	0.67 (1)	-0.75 (51)	-0.03 (30)	-0.66 (58)	0.58 (1)	-0.27 (29)	-1.13 (64)
Kansas City (MO)	MW	Middle America	0.02 (33)	0.02 (24)	-0.21 (47)	-0.63 (47)	0.20 (27)	0.78 (10)	0.41 (31)	-0.07 (22)	-1.19 (68)
Las Vegas (AZ)	W	Containment	-0.69 (54)	0.14 (21)	0.67 (1)	1.29 (9)	0.60 (22)	2.19 (3)	0.58 (1)	-0.27 (29)	-1.25 (69)
Las Vegas (NV)	W	Containment-Lite	-0.94 (61)	-0.18 (32)	0.67 (1)	0.80 (14)	0.12 (28)	-0.11 (44)	-0.54 (62)	1.62 (6)	-0.35 (40)
Los Angeles	W	Growth Management	-0.93 (60)	-0.30 (40)	0.60 (37)	-0.27 (33)	0.77 (16)	-0.70 (59)	0.13 (50)	0.79 (9)	1.97 (4)
Louisville (IN)	MW	Middle America	0.52 (22)	-0.23 (34)	0.67 (1)	-0.65 (48)	-1.06 (63)	-0.04 (41)	0.42 (28)	0.17 (16)	-1.15 (66)

How to Efficiently Fill uncategorized data?

- Our current data set is richer than zoning categories data set.
- What method is best to categorized uncategorized data?
- How do we efficiently find nearest neighbor to match neighboring category?

DiD Model (work in progress)

$$Y_{tj} = \sum_{t=-n}^{n} \theta_{tj} HR_{tj} + \sum_{t=-n}^{n} \phi_{tj} Post_{tj} + \sum_{t=-n}^{n} \psi_{tj}(HR_{tj} \times Post_{tj}) + \gamma_{tj} X_{tj} + \epsilon_{tj}$$

- category j , time i
- Y_{tj} —- change in truck parking capacity
- HR_{tj} —- high restriction index
- $Post_{tj}$ —- represents the indicator for the post-accident period

End. Thank you for reading

References