

Survival of Gentrification / Depreciation in Restaurants

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1 Abstract

2 Introduction

Yelp Dataset Papers:

(?????????????)

Zillow Dataset Papers:

Has previously been combined with the yelp dataset ?.

Our goal is to use the correlation of two time-series:

1. The monthly median rent, as tracked by Zillow Rental Data. 2. The median restaurant review rating (stars) for each restaurant in a neighborhood.

Zillow rental data can be used to detect appreciating, and depreciating neighborhoods.

As rents rise in a given neighborhood, which types of businesses fare / worse better in the reviews? As rents fall in a given neighborhood, which types of business fare / worse better in the reviews?

We hope to present concrete suggestions to restaurant owners to improve the survivability of their businesses in times of strong appreciation / depreciation in the housing market.

3 Data

3.1 Yelp Academic Dataset

The Yelp Academic Dataset contains five files:

1) `yelp_academic_dataset_business.json`

2) `yelp_academic_dataset_review.json`

3) `yelp_academic_dataset_user.json`

4) `yelp_academic_dataset_checkin.json`

The Yelp Dataset Business file includes data on 77,445 businesses in the metro areas of Las Vegas, NV, Phoenix, AZ, Charlotte, NC Pittsburgh, PA Champaign, IL, Kitchener, Canada, Montreal, Canada, Edinburgh, Scotland, Karlsruhe, Germany.

3.2 Zillow Public Dataset

The Zillow Public Dataset (hereafter Zillow dataset) contains many files.

Zillow divides homes into geographic “neighborhoods” with well defined boundaries. The Zillow Home Value Index (ZHVI) is Zillow’s best estimate of median home price in a neighborhood. ZHVI is reported on a monthly basis for 6,958 neighborhoods across the US.

Median rental price for studio, one, two, three, four and five or more bedroom apartments are reported for a smaller set of about 300 neighborhoods.

The Zillow neighborhood boundaries <http://www.zillow.com/howto/api/neighborhood-boundaries.htm>

Each Zillow neighborhood has geographic boundaries, defined in an associated ESRI arcGIS shape file. Boundary information <http://www.zillowgroup.com/news/7000-neighborhood-boundary-Released-in-2008>

ZHVI methodology. <http://www.zillow.com/research/zhvi-methodology-6032/>
(?)

4 Methods

4.1 Combination of Datasets

Each Yelp business is tagged with a geographic (latitude, longitude) coordinate. In this section, we describe how we sort each Yelp business into its appropriate Zillow neighborhood.

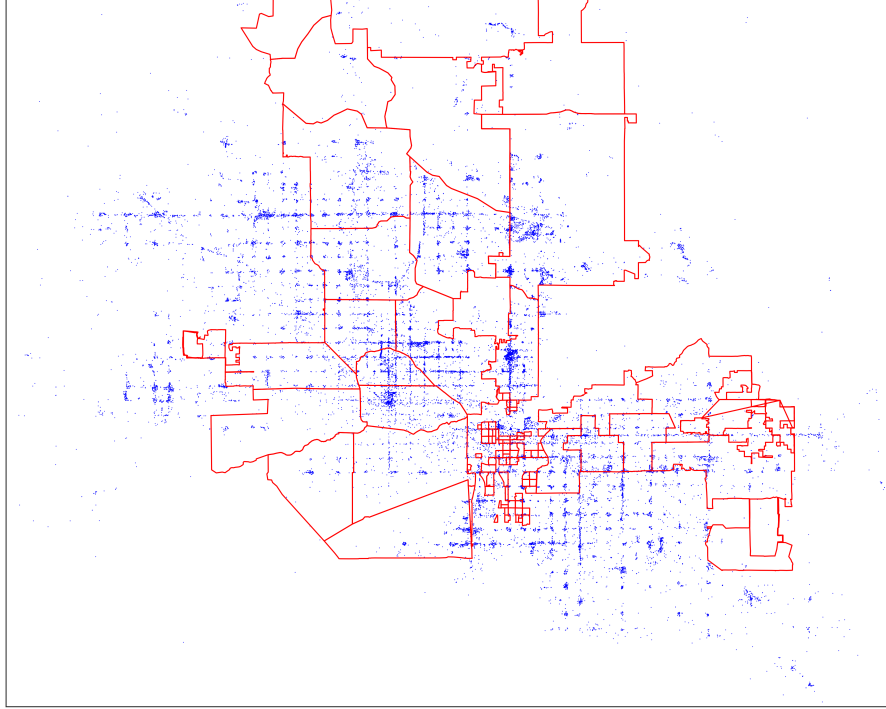


Figure 1: Yelp Businesses (points in blue) and Zillow neighborhood boundaries (lines in red) for the Phoenix, AZ metro area. In §4.1, we describe how we sort each Yelp Business into its appropriate Zillow neighborhood.

To perform this sorting, we employ a two-step approach. In the first step, we test every Yelp business for inclusion in the bounding box of every Zillow neighborhood. In the second step, we test every Yelp business for polygon inclusion in the neighborhoods which bounding boxes it lies within. We use this two-step approach because the first step can rule out all but two or three of the

We introduce the concept of the bounding box which we will define as the smallest range of latitudes and longitudes that include the whole neighborhood polygon. We test each Yelp business for inclusion in the set of 6,958 bounding boxes. In Fig. 2, we see a randomly selected Yelp business, displayed as a red point. We see that this business is included in the bounding boxes of two Zillow neighborhoods.

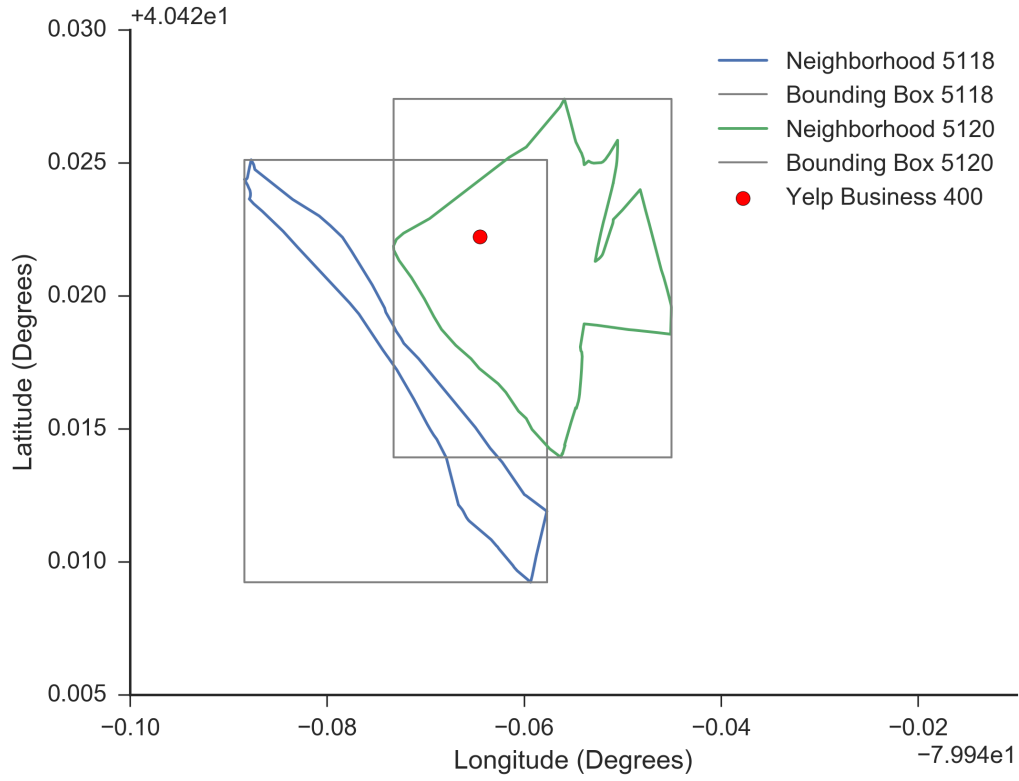


Figure 2: Example of neighborhood and neighborhood bounding box inclusion method. Yelp business 400 (the red point) is included in the bounding boxes of two Zillow neighborhoods. It is only included in one neighborhood polygon, however.

We then test for point-in-polygon inclusion using an implementation of a ray-casting method in `Python (?)`. For each Yelp business, we only test the Zillow neighborhoods whose bounding boxes it lies within.

4.2 Description of Combined Dataset

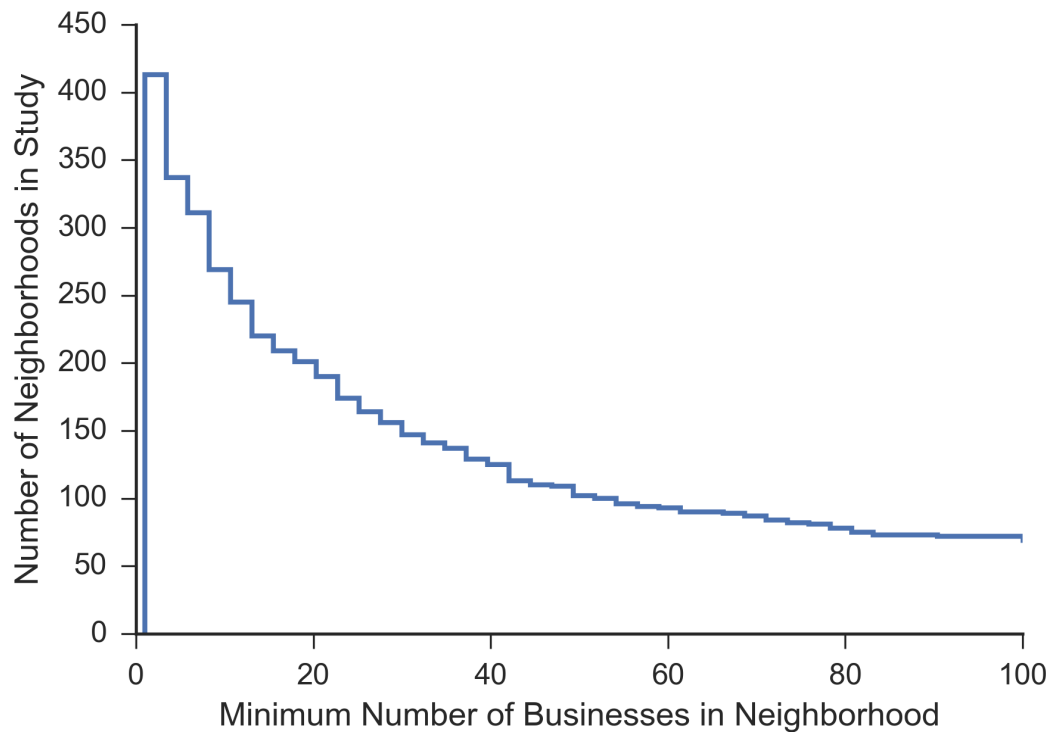


Figure 3:

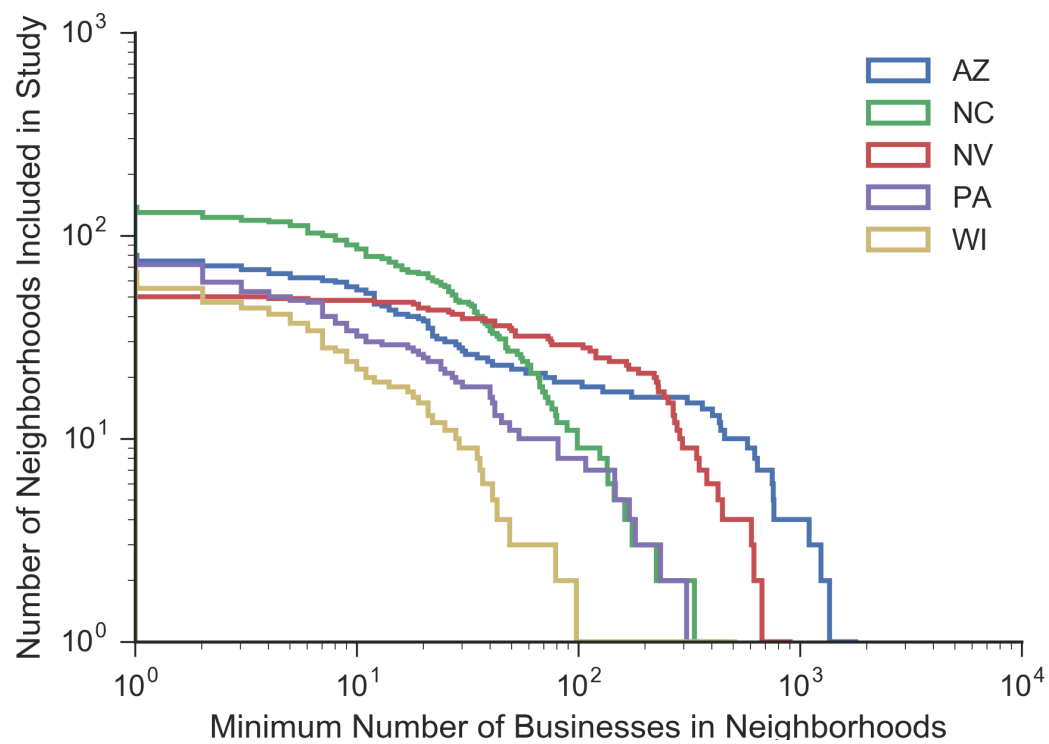


Figure 4:

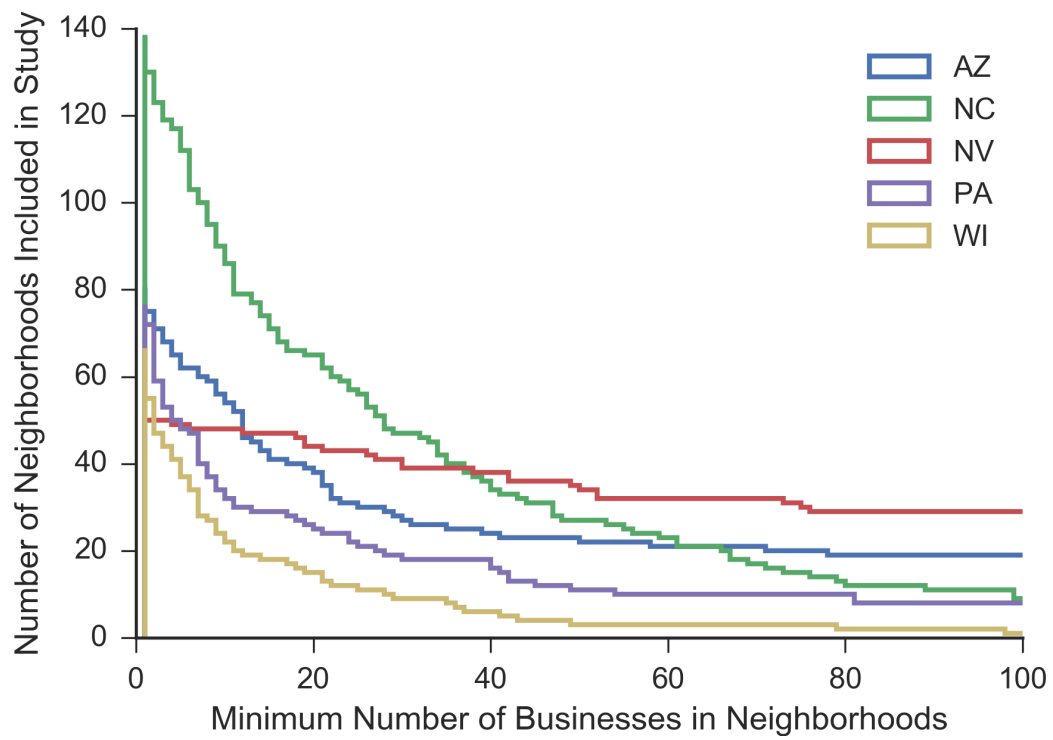


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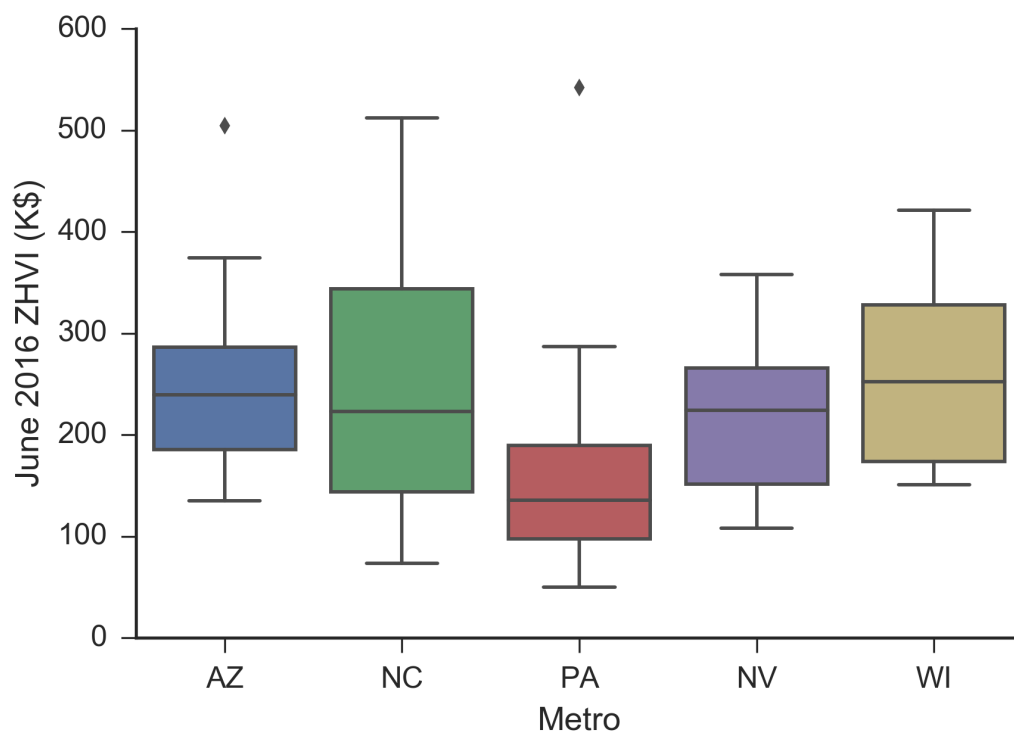


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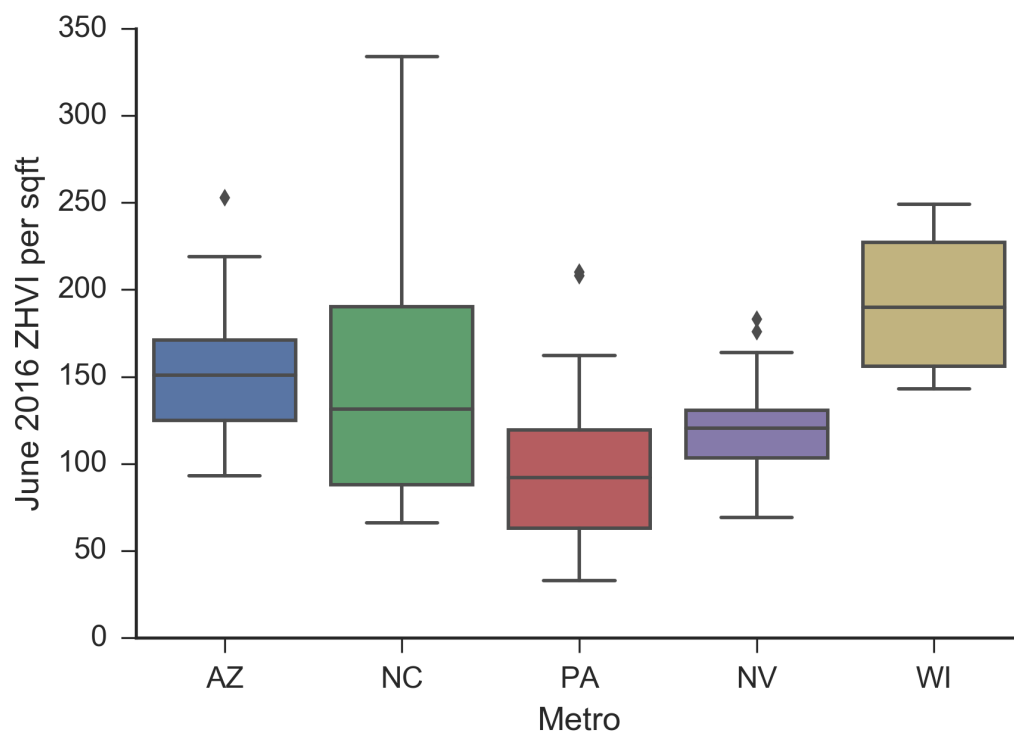


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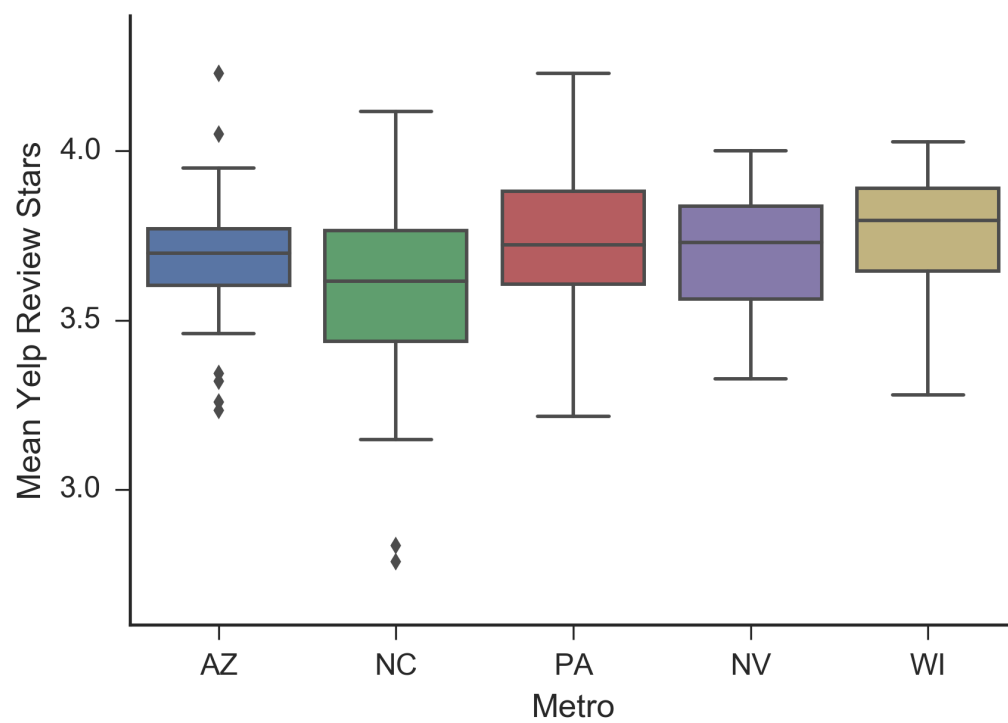


Figure 8:

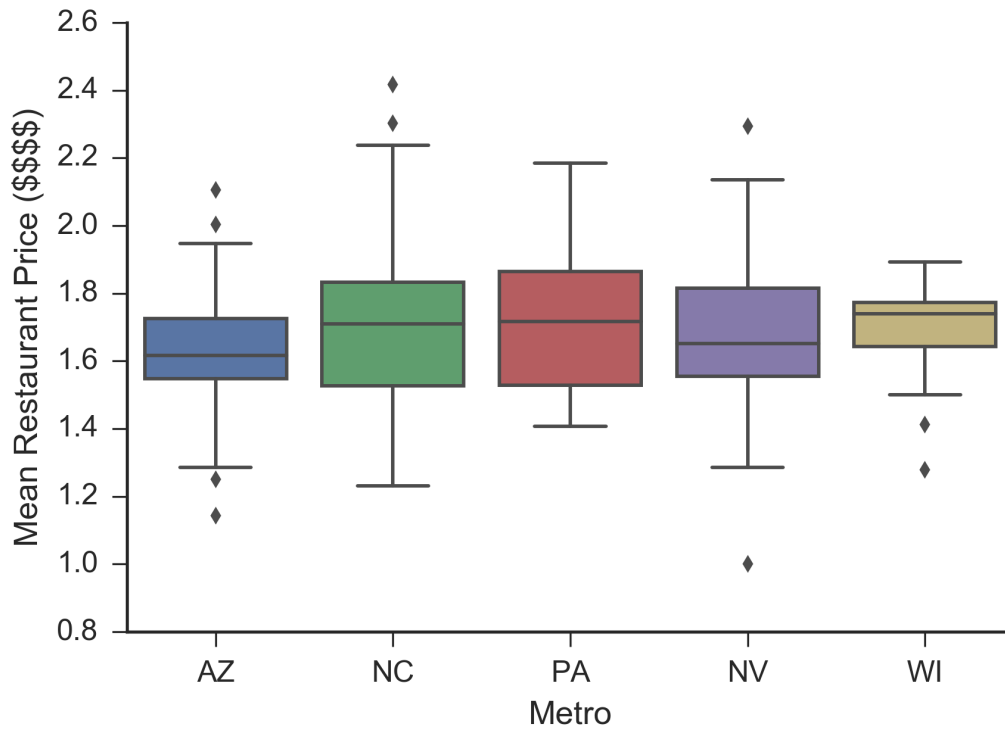


Figure 9:

Metro	Original	Retained	Rate
Phoenix, AZ	32,615	19,958	61.2%
Charlotte, NC	6,162	4,853	78.7%
Las Vegas, NV	21,233	9,694	45.7%
Pittsburgh, PA	3,754	2,749	73.2%
Madison, WI	2,802	1,355	48.3%
Champaign, IL	x	0	0%
Kitchener, Canada	x	0	0%
Montreal, Canada	x	0	0%
Edinburgh, Scotland	x	0	0%
Karlsruhe, Germany	x	0	0%

Table 1: min n = 0

	median	mean	sum	len
state				
AZ	31.609536	62.769432	2636.316160	42
NC	2.776164	3.466144	225.299334	65
NV	11.553754	22.659192	997.004433	44
PA	1.192682	1.586050	41.237288	26
WI	0.057833	0.066647	0.999710	15

Table 4: n = 20

The combined Zillow and Yelp Dataset contains

Metro	median (B/N)	mean (B/N)	Total B	Total N
Phoenix, AZ	116.5	467.6	19,640	42
Charlotte, NC	43.0	66.1	4,296	65
Las Vegas, NV	178.0	218.6	9,619	44
Pittsburgh, PA	43.5	94.8	2,464	26
Madison, WI	36.0	71.4	1,071	15

Table 2: min n = 20

City	median (B/N)	mean (B/N)	Total B	Total N
Charlotte	43.0	66.1	4296	65
Henderson	105.0	153.0	2907	19
Las Vegas	241.5	242.0	5809	24
Madison	36.0	71.4	1071	15
Mesa	491.5	509.5	3057	6
North Las Vegas	903.0	903.0	903	1
Phoenix	625.0	763.30	11450	15
Pittsburgh	43.5	94.8	2464	26
Scottsdale	2100.0	1531.7	4595	3
Tempe	26.5	29.9	538	18

Table 3:

4.3 Determination of Most Common Yelp Categories and Chains

Each Yelp business has user-generated tags, that allow other users to determine what genre the business is. In the full Yelp Dataset, there are 892 distinct categories. In the full Yelp

category	counts
Restaurants	25071
Shopping	11233
Food	9250
Beauty & Spas	6583
Health & Medical	5121
Nightlife	5088
Home Services	4785
Bars	4328
Automotive	4208
Local Services	3468
Active Life	3103
Fashion	3078
Event Planning & Services	2975
Fast Food	2851
Pizza	2657
Mexican	2515
Hotels & Travel	2495
American (Traditional)	2416
Sandwiches	2364
Arts & Entertainment	2271

Table 5: The 20 most common Yelp tags in the Full Dataset ($n = 77,445$).

Dataset ($n = 77,445$)

Each Yelp business has a user-generated name. Many prominent chains have locations in neighborhoods across the country

counts	name
483	Starbucks
365	Subway
345	McDonald's
200	Walgreens
180	Taco Bell
155	Pizza Hut
147	Burger King
144	Wendy's
134	The UPS Store
120	Panda Express
119	Dunkin' Donuts
118	Bank of America
114	Great Clips
108	Wells Fargo Bank
107	Circle K
97	Domino's Pizza
95	Chipotle Mexican Grill
95	Jimmy John's
93	KFC
88	US Post Office

Table 6: The 20 most common Yelp restaurant names in the Full Dataset ($n = 77,445$).

4.4 Yelp Review Description

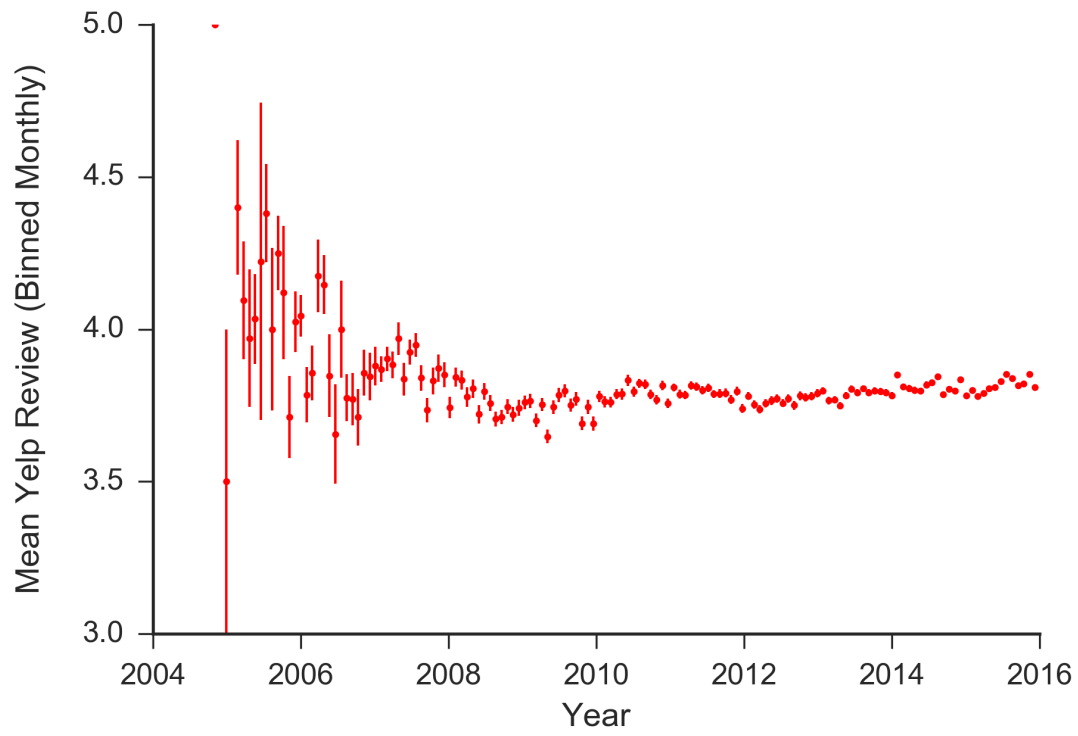


Figure 10:

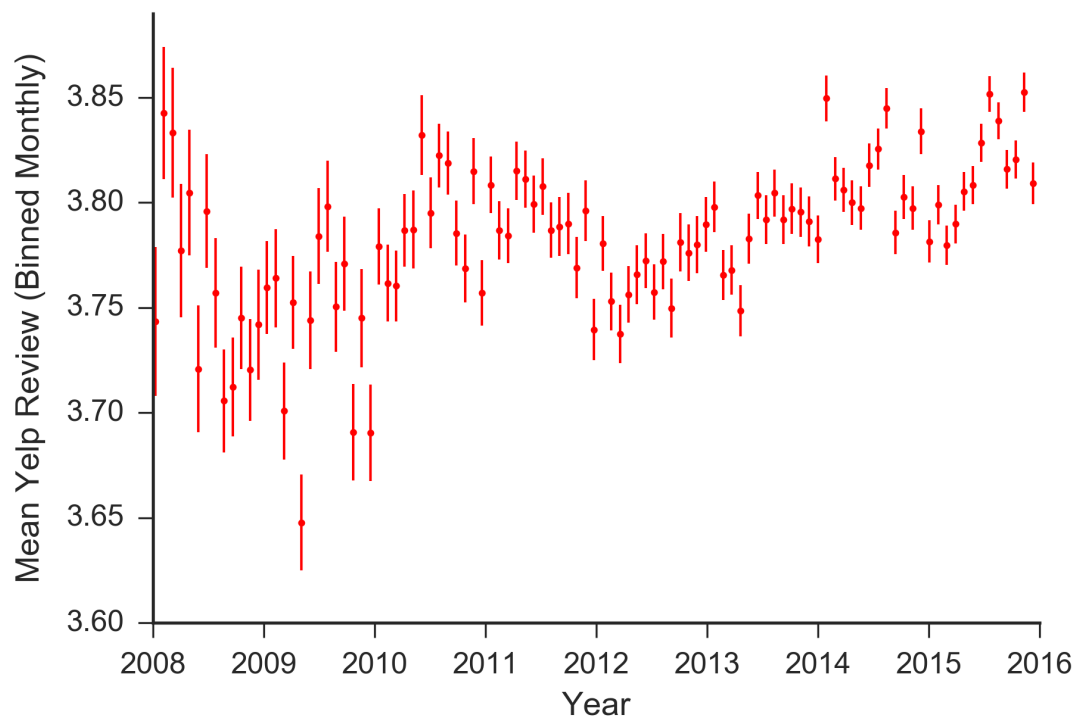


Figure 11:

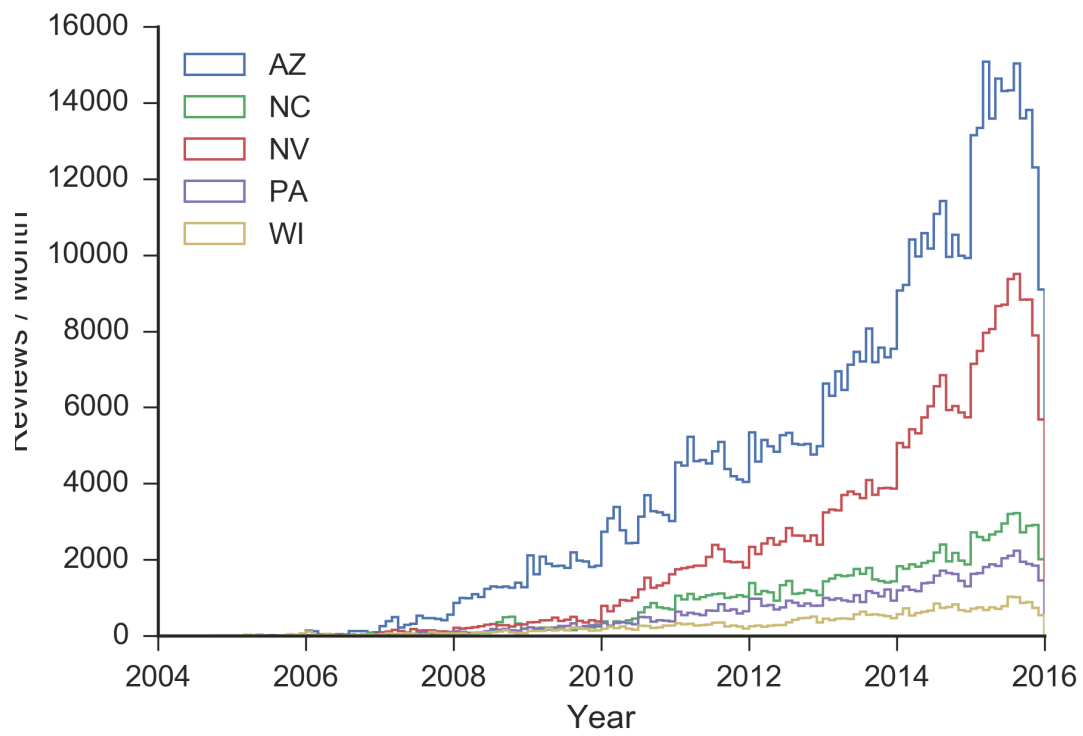


Figure 12:

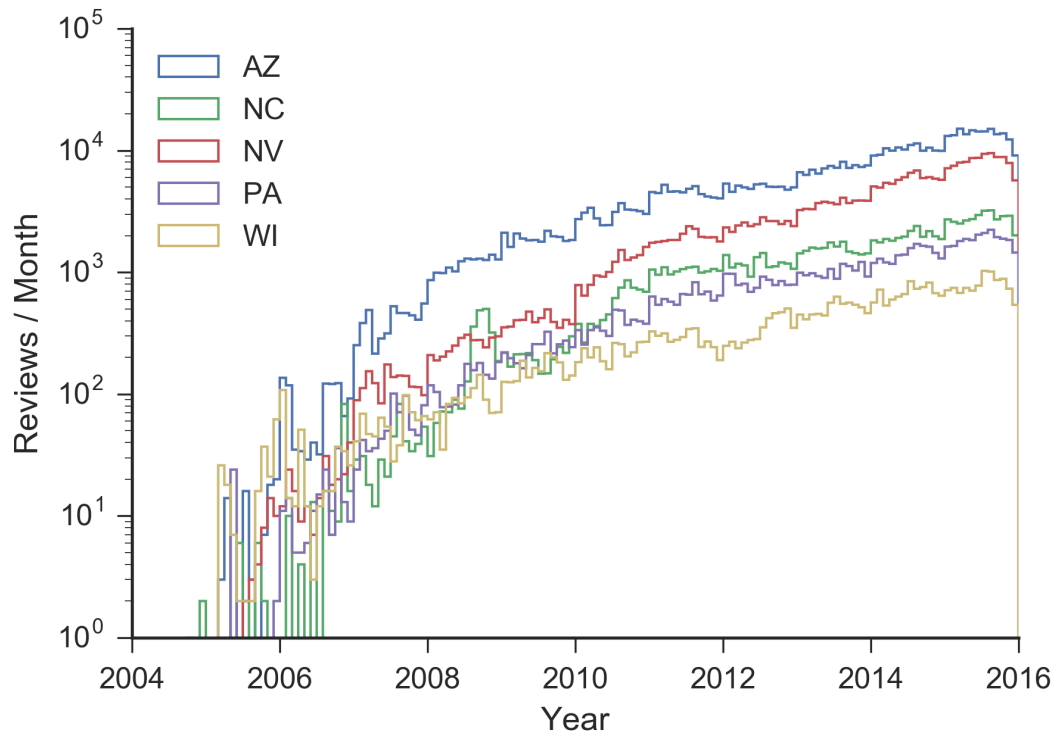


Figure 13:

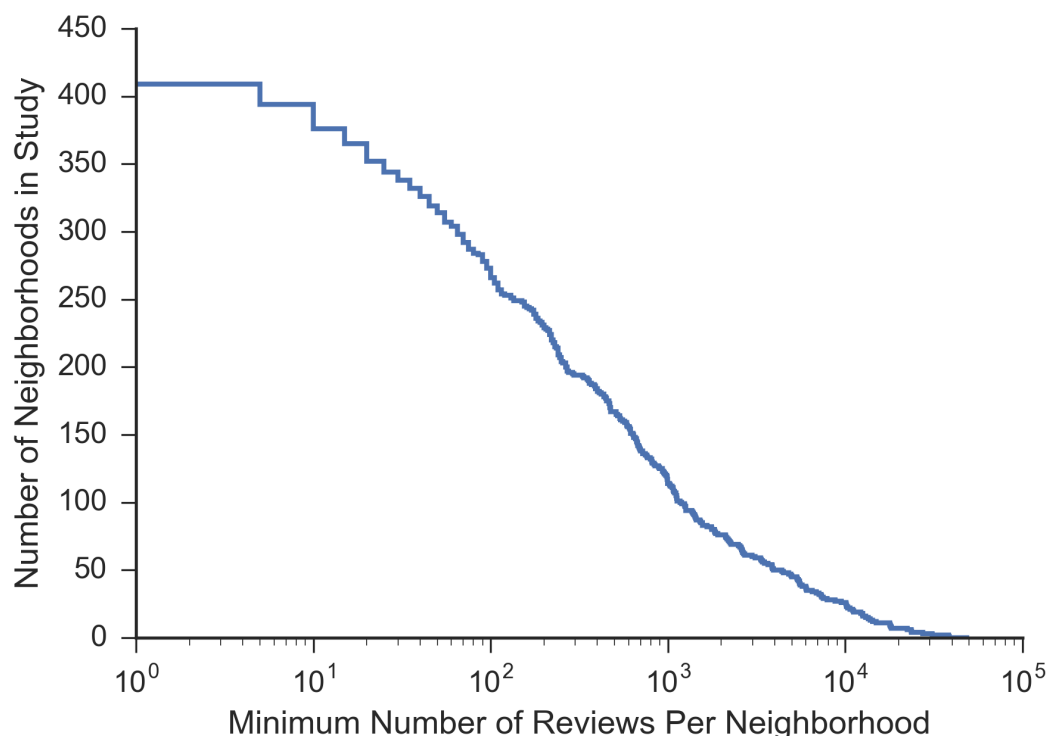


Figure 14:

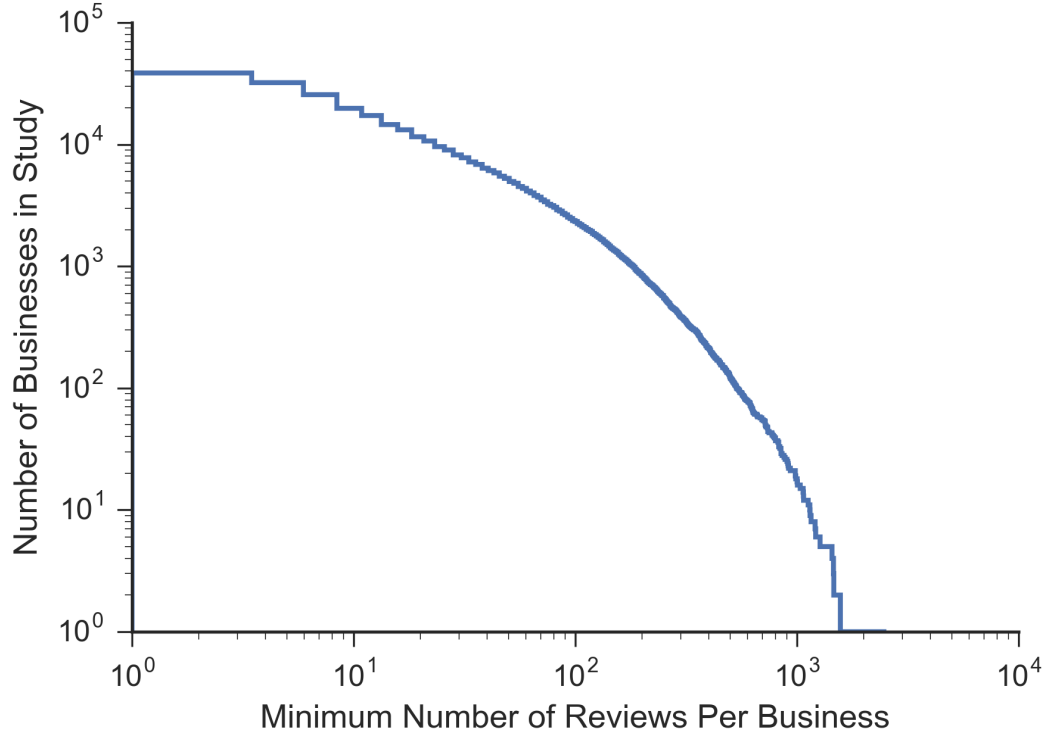


Figure 15:

4.5 Computation of Price Trend

5 Results

Ideas:

1. For each chain, how does chain density (spatial, and fractional) relate to ZHVI.
2. How does “chainy-ness” ($\frac{N_{\text{chain}}}{N_{\text{local}}}$) relate to neighborhood ZHVI / size.
3. For each chain, how does chain review correlate with neighborhood ZHVI / size.

5.1 Statics Results

In this section, we compute static results for each neighborhood.

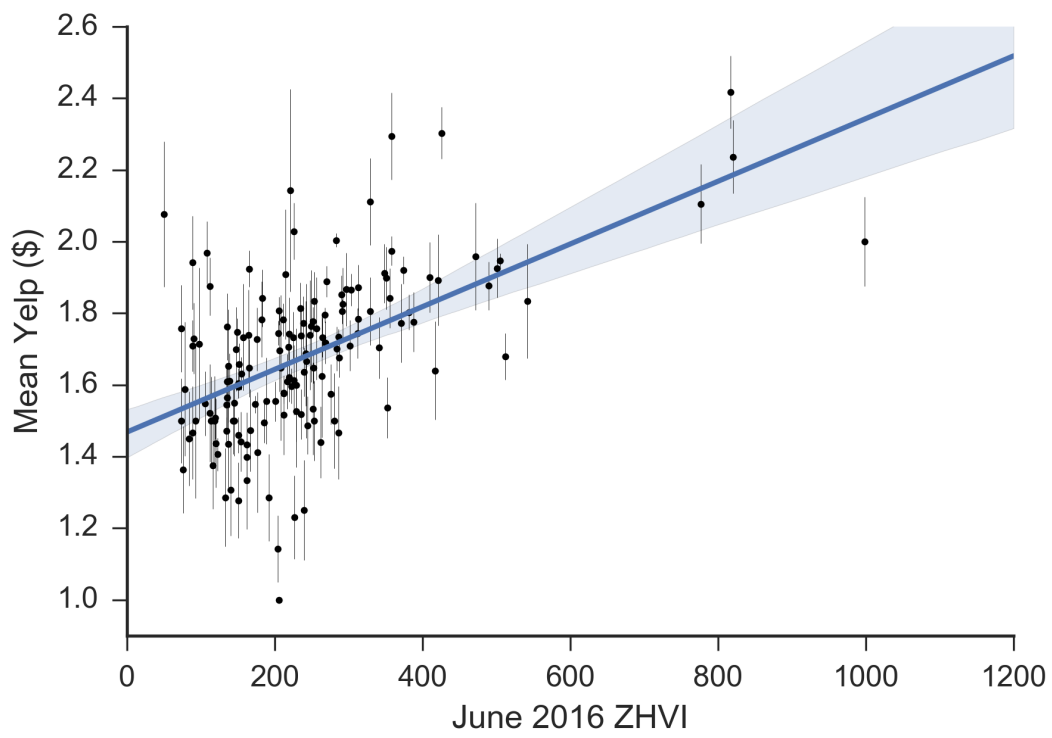


Figure 16:

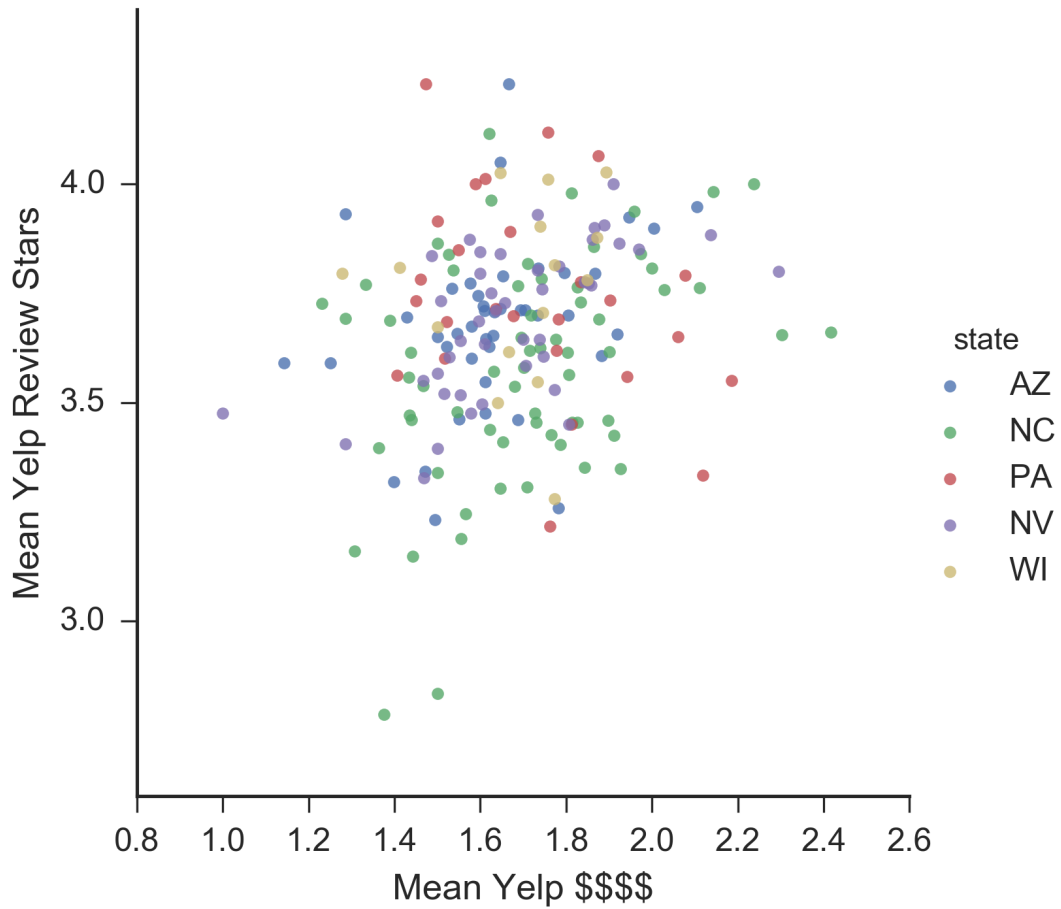


Figure 17:

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